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Research paper

Image denoising using learned dictionaries and K-SVD

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Abstract

The zero-mean white and homogeneous Gaussian additive unwanted signal must be deleted from the known unique image whenever we are going to tackle the image denoising issue. Here the approach that has well thought-out is relying on the sparse and unnecessary representations over trained dictionaries. The valuable image content which depicts in a dictionary is completed by K-SVD algorithm. Here we take two options of training from the tarnished image itself or training on an amount of pure good quality image database. As we know that the K-SVD is confined in managing very small image patches that are extendable in deploy an arbitrary image sizes by defining a global image prior that pressurizes sparsity over patches in all spots of the image. Such a straightforward and efficient denoising algorithm is done by Bayesian treatment. This makes the paper very effectively surpassing all the up to date published papers on image denoising and the situation of art denoising concert is improved.

Keywords: *Image Denoising; K-SVD; Dictionaries.*

1. Introduction

Inherently there exists noise in every digital image. This is frequently introduced by the cameras when a picture is clicked or any other gadgets. whereas this process of considering images we can see many distortions that included in the true original image which is nothing but noise to get rid of this noise we use different techniques to remove noise, which results denoised image not having any unwanted signal or added artifacts.
A lot of research attention done in past few decades on denoising of signals by using redundant representations and sparsity as driving forces. Primarily sparsity of unitary wavelet coefficients is taken and this leads toward celebrated shrinkage algorithm [1]-[5]. The prominent reason to redundant representations was to have shift invariance property. To handle images along with growing realizations that are regularly separable 1-D wavelets not properly, for this the development of various latest tailored multi-scale and directional redundant transforms were set up with curvelet, contourlet, wedgelet, bandlet and steerable wavelet. In equivalent the ability to address image denoising issues as a direct sparse decomposition method over redundant dictionaries is done by using matching pursuit and basis pursuit denoising. Every possibility takes the best possible image denoising schemes till now.
The work presented here refers to the application of learned disctionaries and the modified version of single value decomposition known as k-SVD to image denoising.
Further the paper is organized in four Sections as follows wherein Section 2, a brief description of the proposed techniques is given and the obtained simulation results are given in Section 3. The overall conclusions are given in Section 4.

2. Proposed techniques

2.1. K-SVD

Through singular value decomposition process, we are able to create a dictionary for sparse representations in applied mathematics. K-SVD is a dictionary learning algorithm, which indicates simplification of K-means clustering algorithm is K-SVD which works caluclatively varying in between sparse coding input data based on current dictionary and keep informed the atoms in the dictionary to enhanced data fit. In image processing, audio processing, biology, and document analysis K-SVD [1], [2] is widely in use.
The differences between the textures of neighborhood pixels along small patches, and pixel region are showed in [4], [5] computer vision field recently. As we know that different types of FLLs mainly visible different intensity variance, which means that there are various textures for different types of FLLs. Thus, this study explores patches locally (texture structures) as local descriptors in the codebook model.
Given an image and the patch region with size centered at the k^{th} pixel, we directly use intensities, of all pixels in the patch regions as a local descriptor. The representation of a pixel directly uses the neighboring pixels' intensities, which not only considers the intensity but also retains the variation in intensity (texture) without any detained structure loss and thus would adapt to the fine-grained medial FLL retrieval application. In our study, we take the local patches of all pixels in a medical image as the local descriptor set for coding.

2.2. Codebook learning algorithm: from k-means to sparse coding

Given a set of prepared local descriptors, the codebook model firstly learns a small set of visual words (prototype features) for coding any local descriptor. A common strategy for codebook learning in the BoVW model usually applies the K-means algorithm. A family of signals is represented by the nearest neighbor in a code book, in which a codeword is a column vector. The codebook is learned in the K-means algorithm by solving the least-square problem as followed and refers to -norm and -norm, separately. Are the coded vectors for Single nonzero entry in each coded vector is ensured by the constraint, and the coding weight is always 1, formulated as the second constraint term: The K-means is widely used in codebook training due of its simplicity. However, it is too restricted to approximate signals properly by allowing only one codeword from the codebook.

Generalization of K-means algorithm provides sparse coding technique employs a linear combination of code words for the representation of each signal, which means more than one nonzero entries in coding, and the weights can be calculated to be arbitrary values but not limited to 1. The intuitive way for the sparse coding problem is formulated and optimizes the following objective function. Where the sparse approximation of on code book is a sparsity measure, which is a ratio between the number of nonzero entries in and the whole number of code words in it controls the maximum number of code words that can be used for approximation of the input signal.

The coefficient calculation is implemented via OMP algorithm; this part mainly describes the atom updating procedure, where each of the code words will be updated once a time, assuming that all the other code words and the coded vector are fixed. The update of the kth atom is done by amending penalty term as

$$\|Y - DX\|^2 = \left\|\left(Y - \sum_{j\neq k}^{K} d_j x_k^T\right) - d_k x_k^T\right\|^2 = \|E_k - d_k x_k^T\|^2$$

Where the total number of code words and row vector contains the coefficients of all input signals on codeword. Represents the reconstruction residuals using all codeword's excepting. After addition of approximating the input signals, we expect that the reconstruction error in the equation is minimized with the fixed, which is formulated as the following formula:

$$\operatorname{argmin}\|E_k - d_k x_k^T\|^2$$

3. Results

Here the demonstration of the results for all above three schemes on various tests images and several dictionaries are done with testing of noise levels with similar ones that used in denoising experiments to enable a fair difference. The DCT dictionary results global trained history and spoiled images training directly are summarized in table -1. This referred as adaptive dictionary there on. The dictionary is 64256 in all set of experiments, which handles image patches of size 8×8 pixels. The various realizations of noise show an average of each result reports mentioned in above 5 experiments.

The left portion of the figure shows the redundant DCT dictionary with every atom as 8×8 size of the pixel. This is used to start of training algorithms that follow. K-SVD algorithm produces the data set of 100000 8×8 patches in a global trained dictionary shown in right side of the image. The Fig3 shows the patches which were considered from arbitrary set of clean usual images.

A sparse coding of every patch having size 8×8 form spoiled image is considered in every experiment. Whenever the threshold crosses the mean error, the accumulation of atoms was done using OMP, by choosing empirically $\epsilon=1.15.\sigma$. This shows that our proposed algorithm assumes knowledge of σ. The number of patches $(256-7)^2 = 62001$ includes in every experiment show overlapping of training the dictionary over scraps from noise itself. Later step by step procedure is applied on Fig. 1.

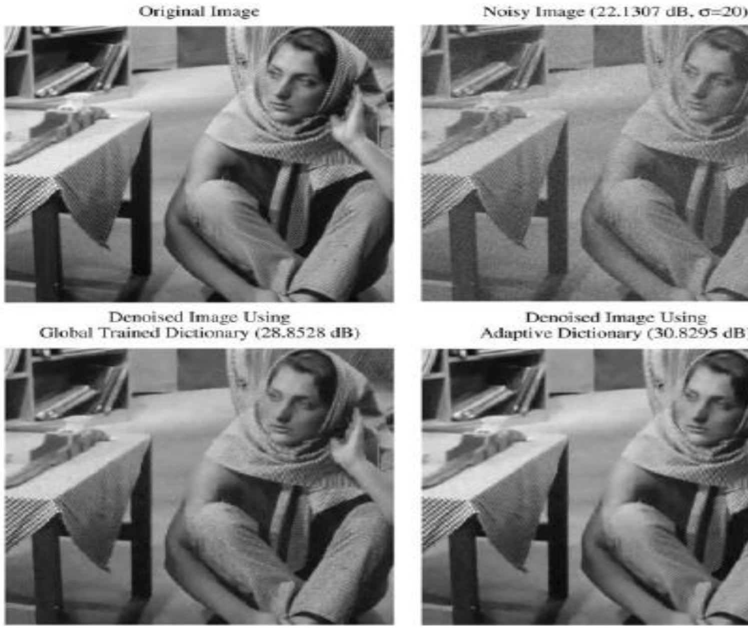

Fig. 1: Resultant Images.

4. Conclusion

Here a new method of denoising is presented, leading to state of art performance which is correspondent and at times crossing the recent published choices. This method is wholly dependent on the local operations and sparse decomposition of every image blocks under one predetermined over complete dictionary with simple mean evaluations. The most important in denoising image is content of the dictionary. Here the performance of the natural real images and the trained patches of the noisy images perform well in proposed system.

For a better pursuit scheme there are many research schemes that currently consider using various dictionaries by switching the optimizing parameters, content and put back the OMP by best method. We also take multi-scale analysis beyond this technique to concentrate on small patched images. For complete overlooking of global structure of the image we exploit multi-scale analysis as well. This shows that K-SVD is not applicable straight forwardly on larger blocks but we are looking to extend these to multi-scale dictionaries.

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