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Image Restoration Using Sparse Dictionary Matrix Learning K-SVD Algorithm

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Abstract: *The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera miss focus. In cases like motion blur, it is possible to come up with a very good estimate of the actual blurring function and "undo" the blur to restore the original image. In cases where the image is corrupted by noise, the best we may hope to do is to compensate for the degradation it caused. In this project, we will introduce and implement several of the methods used in the image processing world to restore image dictionary learning algorithm*

I. Introduction

Sparse Representation

In the last decade, sparsity has emerged as one of the leading concepts in a wide range of signal-processing applications (restoration, feature extraction, compression, to name only a few applications). Sparsity has long been an attractive theoretical and practical signal property in many areas of applied mathematics (such as computational harmonic analysis, statistical estimation, and theoretical signal processing). Recently, researchers spanning a wide range of viewpoints have advocated the use of over complete signal representations [5]. Such representations differ from the more traditional representations because they offer a wider range of generating elements (called *atoms*).

B. Strictly Sparse Signals / Images

A signal x, considered as a vector in a finite-dimensional subspace of $x = [x[1], \ldots\ldots .x[N]]$, is strictly or exactly sparse if most of its entries are equal to zero, that is, if its support $\Delta(x) = \{1 \le i \le N \mid x[i\,] \neq 0\}$ is of cardinality $k << N$. A k-sparse signal is a signal for which exactly k samples have a nonzero value. If a signal is not sparse, it may be sparsified in an appropriate transform domain. For instance, if x is a sine, it is clearly not sparse, but its Fourier transform is extremely sparse (actually, 1-sparse).

More generally, we can model a signal x as the linear combination of T elementary waveforms, also called signal atoms, such that

$$x = \varphi\alpha = \sum_{i=1}^{T} \alpha[i]\varphi_i \qquad (1)$$

In approximation methods, typical norms used for measuring the deviation are the -norms for p=1,2,….. In this paper, we shall concentrate on the case p=2. If n<< k and D is a full-rank matrix, an infinite number of solutions are available for the representation problem, hence constraints on the solution must be set. The solution with the fewest number of non zero coefficients is certainly an appealing representation. This sparsest representation is the solution of either

$$(P_0)\ \min_x \|x\|_0 \text{ subject to } y=Dx \qquad (2)$$

Where is the norm, counting the nonzero entries of a vector.

C. Sparse Coding

Sparse coding is the process of computing the representation coefficients X based on the given signal Y and the dictionary D. This process, commonly referred to as "atom decomposition," requires solving 1 & 2 equations, and this is typically done by a "pursuit algorithm" that finds an approximate solution. Exact determination of sparsest representations proves to be an NP-hard problem. The simplest ones are the matching

pursuit (MP) and the orthogonal matching pursuit (OMP) algorithms. These are greedy algorithms that select the dictionary atoms sequentially.
A second well-known pursuit approach is the basis pursuit (BP). It suggests a convexification of the problems

II. Existing Method:

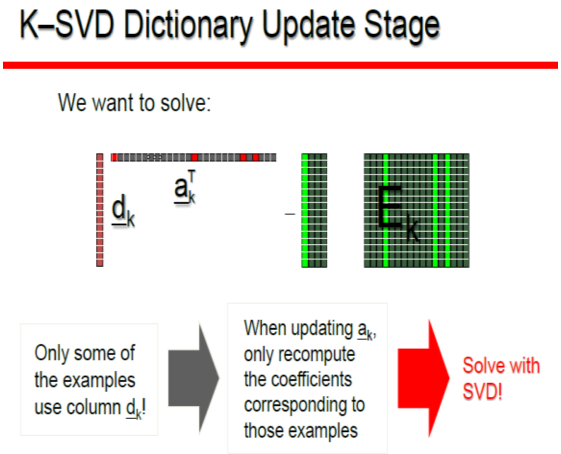
- Block-Matching,
- Discrete Cosine Transform
- Image de-noising in spatial domain
- Edge Detection.
- Image De-blurring Using Wiener Filter
- Image De-noising Using Wavelet Transform based Anisotropic Diffusion Filter

Drawbacks:

- The filters can't efficiently suppress the noise in grayscale images
- The Block-Matching can't preserving edges and fine features
- DCT method fails to give more details about edges in all orientation

III. Design Of Dictionaries

We now come to the main topic of the paper, the training of dictionaries based on a set of examples. Given such a $Y=\{y_i\}_{i=1}^{N}$, we assume that there exists a dictionary D that gave rise to the given signal examples via sparse combinations, i.e., we assume that there exists D, so that solving (p0) for each example yk gives a sparse representation x.



A. Generalizing K-Means

There is an intriguing relation between sparse representations and clustering .In clustering, a set of descriptive Vectors $\{d_k\}_{k=1}^{K}$ is learned, and each sample is represented by one of those vectors. There is a variant of the vector quantization (VQ) coding method, called gain-shape VQ, where this coefficient is allowed to vary. In contrast, in sparse representations as discussed in this paper, each example is represented as a linear combination of several vectors $\{d_k\}_{k=1}^{K}$

Since the K -means algorithm (also known as the generalized Lloyd algorithm-GLA) is the most commonly used procedure for training in the vector quantization setting; it is natural to consider generalizations of this algorithm when
Turning to the problem of dictionary training. Here we shall briefly mention that the K-means process applies two steps per each iteration:

i) given $\{d_k\}_{k=1}^{K}$, assign the training examples to their nearest neighbor; and

ii) given that assignment, update $\{d_k\}_{k=1}^{K}$ to better fit the examples.

B. Maximum Likelihood Methods

The methods reported in use probabilistic reasoning in the construction of D. The proposed model suggests that for every example the relation

$$y = Dx + v \quad (3)$$

Holds true with a sparse representation x and Gaussian white residual vector v with variance σ^2 Given the examples, $Y = \{y_i\}_{i=1}^{N}$, these works consider the likelihood function P(Y|D) and seek the dictionary that maximizes it. Two assumptions are required in order to proceed: the first is that the measurements are drawn independently, readily

providing

$$P(Y|D) = \prod_{i=1}^{N} P(y_i|D) \quad (4)$$

The second assumption is critical and refers to the “hidden variable” X. The ingredients of the likelihood function are computed using the relation

$$P(y_i|D) = \int P(y_i, x|D)dx = \int P(y_i|x, D).P(x)dx \quad (5)$$

Returning to the initial assumption, we have

$$P(y_i|x, D) = const.\exp\left(\frac{1}{2\sigma^2}\|Dx - y_i\|^2\right) \quad (6)$$

The prior distribution of the representation vector x is assumed to be such that the entries of x are zero mean i.i.d., with Cauchy or Laplace distributions. Assuming for example a Laplace distribution, we get

$$P(y_i|D) = \int P(y_i, x|D)dx = \int P(y_i|x, D).P(x)dx$$

$$= const. \int \exp\{\frac{1}{2\sigma^2}\|Dx - y_i\|^2\}.\exp.\{\lambda\|x\|\}dx \quad (7)$$

This integration over x is difficult to evaluate, and indeed, Olshausen and Field handled this by replacing it with the external value of $P(y_i|x, D)$. The overall problem turns into

$$D = argmax_D \sum_{i=1}^{N} max_{xi}\{P(y_i, x_i|D)\} \quad (8)$$

This problem does not penalize the entriesof D as it does for those of. An iterative method was suggested for solving above equation. It includes two main steps in each iteration:

i) Calculate the coefficients using a simple gradient descent procedure and then

ii) Update the dictionary

C. The MOD Method

An appealing dictionary training algorithm, named *method of optimal directions* (MOD), is presented by Engan. This method follows more closely the k-means outline, with a sparse coding stage that uses either OMP or FOCUSS followed by an update of the dictionary. The main contribution of the MOD method is its simple way of updating the dictionary. Assuming that the sparse coding for each example is known, we define the errors. The overall representation mean square error is given by

$$\|E\|_F^2 = \|[e1, e2, \ldots, eN]\|_F^2 = \|Y - DX\|_F^2 \quad (9)$$

We have concatenated all the examples yi as columns of the matrix Y and similarly gathered the representations coefficient vectors xi to build the matrix X.

D. Maximum A-Posteriori Probability Approach

The same researchers that conceived the MOD method also suggested a MAP probability setting for the training of dictionaries, attempting to merge the efficiency of the MOD with a natural way to take into account preferences in the recovered dictionary.. However, rather than working with the likelihood function P(Y|D), the posterior P(D|Y) is used. Using Bayes’ rule, we have P(D|Y) α P(Y|D)P(D) , and thus we can use the likelihood expression as before and add a prior on the dictionary as a new ingredient. When no prior is chosen, the update formula is the very one used by Olshausen and Field. A prior that constrains D to have a unit Frobenius norm leads to the update formula

$$D^{(n+1)} = D^{n} + \eta_n E X^T + \eta_n tr(X E^T D^{(n)}) D^{(n)} \quad (10)$$

The last term compensates for deviations from the constraint. This case allows different columns in D have different norm values. As a consequence, columns with small norm values tend to be underused, as the coefficients they need are larger and as such more penalized. Compared to the MOD, this line of work provides slower training algorithms.

IV. The K-SVD Algorithm

This algorithm is flexible and works in conjunction with any pursuit algorithm. It is simple and designed to be a truly direct generalization of the k-means. As such, when forced to work with one atom per signal, it trains a dictionary for the gain-shape VQ. When forced to have a unit coefficient for this atom, it exactly reproduces the K–means algorithm. The KSVD is highly efficient, due to an effective sparse coding and a Gauss–Seidel-like accelerated dictionary update method. The algorithm's steps are coherent with each other, both working towards the minimization of a clear overall objective function.

A. K-SVD Algorithm **Goal:** To find the best dictionary to represent the data sample $Y = \{y_i\}_{i=1}^{N}$ as sparse decompositions.

$$\min_{D,X}\{\|Y - DX\|_F^2\} \text{ subject to } \forall i \; \|x_i\|_0 \leq T_0.$$

Initialization: Set the dictionary matrix $D^{(0)} \in R^{n \times K}$ with l^2 normalized columns. Set J=1.Repeat until convergence Sparse coding stage: Use any pursuit algorithm to compute the representation vectors xi for each example yi by

Approximating the solution of i =1,2,……..N, $i=1,2,\ldots\ldots N, \min_{x_i}\{\|y_i - Dx_i\|_2^2\}$ subjected to $\|x_i\|_0 \leq T_0$.

Codebook update stage: For each column k=1,2,....k in $D^{(J-1)}$ update it by

1.Define the group of examples

that use this atom,wk={i| 1≤i ≤ N, (i)≠0}.

2. Compute the overall representation error matrix $E_k = Y - \sum_{j \neq k} d_j x_T^j$

3.Restrict Ek by choosing only the columns corresponding to wk and obtain Ek^R

4.Apply SVD decomposition Ek^R= udv^T Choose the updated dictionary column dk to be the first column of U. Update the coefficient vector to be the first column of V multiplied by D(1,1). Set J=J+1.

B. K-SVD Implementation Detail

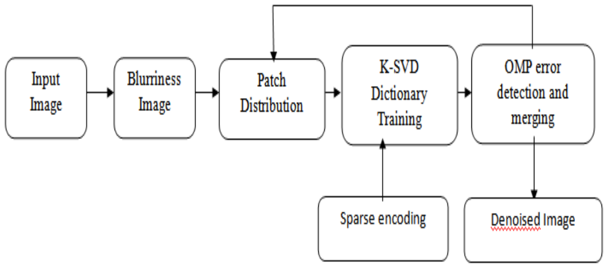
1) When using approximation methods with a fixed number of coefficients, we found that FOCUSS proves to be the best in terms of getting the best out of each iteration. However, from a run-time point of view, OMP was found to lead to far

More efficient overall algorithm

2) When a dictionary element is not being used "enough" it could be replaced with the least represented signal element, after being normalized. Since the number of data elements is much larger than the number of dictionary elements, and since our model assumption suggests that the dictionary atoms are of equal importance, such replacement is very effective in avoiding local minima and over fitting.

3) Similar to the idea of removal of unpopular elements from the dictionary, we found that it is very effective to prune the dictionary from having too-close elements. If indeed such a pair of atoms is found, one of those elements should be removed and replaced with the least represented signal element.

Block Diagram



SPARSE DICTIONARY LEARNING

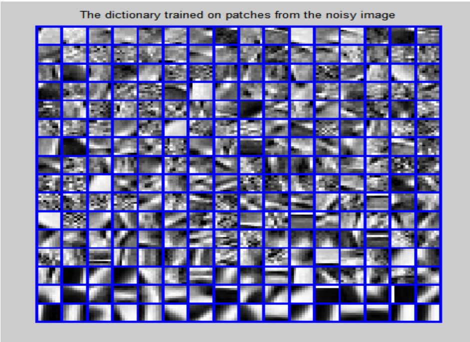
Sparse dictionary learning is a representation learning method which aims at finding a sparse representation of the input data (also known as sparse coding) in the form of a linear combination of basic elements as well as those basic elements themselves.

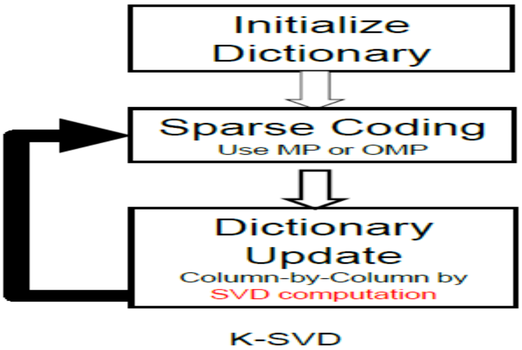
These elements are called atoms and they compose a dictionary. Atoms in the dictionary are not required to be orthogonal, and they may be an over-complete spanning set.

This problem setup also allows the dimensionality of the signals being represented to be higher than the one of the signals being observed. The above two properties lead to having seemingly redundant atoms that allow multiple representations of the same signal but also provide an improvement in sparsity and flexibility of the representation.

Dictionary learning

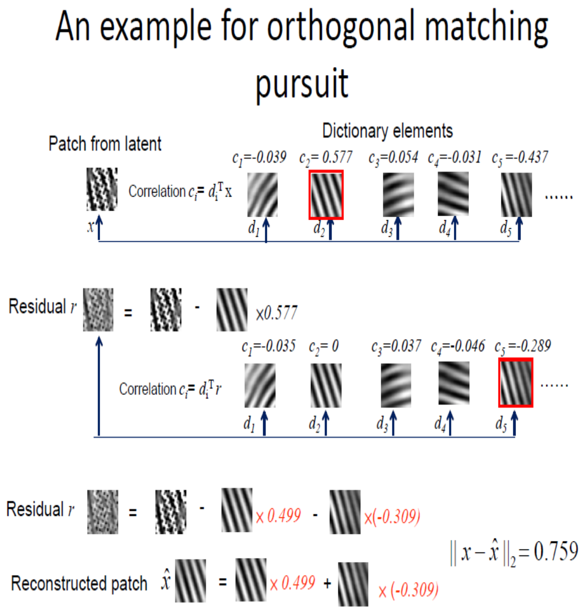
The resulting dictionary is in general a dense matrix, and its manipulation can be computationally costly both at the learning stage and later in the usage of this dictionary, for tasks such as sparse coding. Dictionary learning is thus limited to relatively small-scale problems. Inspired by usual fast transforms, we proposed a general dictionary structure that allows cheaper manipulation, and an algorithm to learn such dictionaries –and their fast implementation– over training data. The approach was demonstrated experimentally with the factorization of the Hadamard matrix and with synthetic dictionary learning experiments





ORTHOGONAL MATCHING PURSUIT

Orthogonal matching pursuit algorithm, the correlation coefficient of atoms and the residual error are calculated, and the Dice similarity coefficient is introduced and used as a new principle to select atoms from the atom library. Thus it can improve the accuracy of color-information replication effectively, and high-accuracy reproduction of color information can be realized. Principal Components on the Accuracy of Spectral-reflectance Reconstruction



Advantages

- ❖ It gives the better signal to noise ratio and preserves the image edges and textures
- ❖ The noise coefficients can be analyzed easily by component based techniques.
- ❖ The shrinkage method will be suppressed the noise effectively from the natural images.

Application

- ❖ Security Process on Toll Gate (License Plate Verification) Application
- ❖ Medical Application
- ❖ Photoshop Application

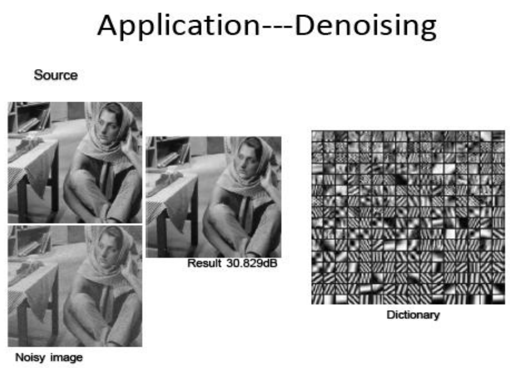
Software Requirements

- ❖ MATLAB 2013a

V. Conclusion

In this paper, we addressed the problem of generating and using over complete dictionaries. We proved that K-SVD algorithm is the best for training an over complete dictionary that best suits a set of given signals. This algorithm is a generalization of the K-means, designed to solve a similar but constrained problem. We have shown that the dictionary found by the K-SVD performs well for both synthetic and real and outperforms alternatives such as the no decimated Haar and overcomplete or unitary DCT.

OUTPUT



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