Image Denoising based on Multi-Scale Dictionary Learning and Cuckoo Search Algorithm

Hassan Al-Eraky*, Ahmed Mohamed Abas, and Mohamed Talaat Ali

Computer Department, Deanship of Preparatory Year and Supporting Studies, Imam Abdulrahman bin Faisal University, Dammam, Saudi Arabia
*haeleraky@iau.edu.sa

Abstract: We present a new approach to solve image denoising problem by using a combination of sparse coding and swarm optimization algorithms. One of the most recent approaches to solve image denoising problem is sparse decomposition over redundant dictionaries. In sparse coding we represent signals as a linear combination of a redundant dictionary atoms. In this paper we propose an algorithm for image denoising based on Multi-Scale Dictionary Learning (MSDL) and Cuckoo Search (CS) algorithm. In this method the dictionary is learned first by using observed images, then it applies a sparse representation algorithm to reconstruct the target image by using the constructed dictionary. In the learning step we select special atoms from the dictionary, then use the CS algorithm to update the dictionary atoms. Experiments confirms that our proposed algorithm produce state-of-the-art denoising results.

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1. Introduction

Images always contaminated with noise in the image acquisition process and transmission phases, and denoising is the process of reconstructing the image without affecting the important image features as much as possible. Commonly, noise removal has been done by using many denoising schemes, from the earlier smoothing filters like adaptive Wiener filter to the frequency domain denoising methods [1] to the lately developed methods which uses multi-scale and directional transformations like wavelet, curvelet and ridgelet[2-5]

The success of the multi-scale models is due to the tendency of images to become sparse in the transform domain, which implies that the image can be represented by using a small subset of the orthonormal basis like wavelets, curvelets, and contourlets. Although multi-scale transformations likewavelet transform WT has demonstrated its efficiency in denoising, it uses a fixed wavelet basis (with dilation and translation) to represent the image. For natural images, however, there is a rich amount of different local structural patterns, which cannot be well represented by using only one fixed wavelet basis. Therefore, WT-based methods can introduce many visual artifacts in the denoising output.

One of the WT drawbacks when representing an image with a rich number of local features is that only one fixed dictionary cannot represent well all this local feature and some artifacts will appear in the denoised image.

To overcome this drawback in wavelet transform, a dictionary learning method had been proposed to learn the dictionary from the data instead of using fixed dictionary. Elad and Aharon[6, 7] proposed sparse redundant representation and K-SVD based denoising algorithm by training a highly over-complete dictionary. Foi et al.[8] applied a shape-adaptive discrete cosine transform (DCT) to the neighborhood, which can achieve very sparse representation of the image and hence lead to effective denoising. Hassan et al. [9] proposed an algorithm SR-NNMF to enhance the updating process of the learning by using the Non-Negative Matrix Factorization. An off-line dictionary construction methodology (where a dictionary with real-worldwaveforms is initially built and then directly used for Compressed Sensing and sparse modelling without any further modification) was recently proposed by Fira et al. [10].

In this paper, we describe an efficient method for learning an over complete and multi-scale dictionary, for sparse image representation by using a noised version of the source image. The proposed approach designs a multi-scale dictionary, with the dictionary atoms learned for different image scales. The design of the dictionary focuses on the pattern similarity and uniqueness of corresponding atoms in different scales. We applied the proposed method in image denoising under different levels of noise and compare the results with other methods which used for image denoising.

2. Sparse signal representation

Sparse representations for signals become one of the hot topics in signal and image processing in recent years. It can represent a given signal $x \in R^n$ as a linear combination of few atoms in an over complete dictionary matrix $A \in R^{n \times K}$ that contains K atoms $\{a_i\}_{i=1}^{K}$ (K>n). The representation of x may be exact $x = A\alpha$ or approximate, $x \approx A\alpha$, satisfying $\|x - A\alpha\|_p \le \varepsilon$, where the vector α is the sparse representation for the vector x.

To find s we need to solve either

$$(P_0)\ \min_{\alpha} \|\alpha\|_0 \text{ subject to } x = A\alpha \tag{1}$$

Or

$$(P_{0,\varepsilon})\ \min_{\alpha} \|\alpha\|_0 \text{ subject to } \|x - A\alpha\|_2 \le \varepsilon \tag{2},$$

where $\|\ \|_0$ is the l_0 norm, the number on non-zero elements.

The best dictionary is the one which capture the main component of the image and minimizes the norm between the source image and the reconstructed image, on the other hand the best coding is the sparsest one with the best reconstruction capability.

3. Cuckoo Search Algorithm

Cuckoo search firstly introduced by Yang and Deb in 2009 [11], Cuckoo search algorithm is an evolutionary optimization algorithm inspired by the cuckoo bird. In the following section, we will illustrate the main concepts and structure of the cuckoo search algorithm as follow.

3.1 The behavior of cuckoo breading

Recently CS algorithm has been applied in many areas such as function optimization, image processing, scheduling, planning, feature selection, forecasting, and real-world applications. Cuckoo search algorithmis a swarm intelligence algorithm which is used for solving optimization problems. The CS algorithm is a nature-inspired metaheuristic algorithm inspired from the specific egg laying and breeding of cuckoos itself, along with Levy flights random walks. The cuckoo birds lay their eggs in a communal nest and they may remove other's eggs to increase the probability of hatching their own eggs [12]. This method of laying the eggs in other's nests is called obligate brood parasitism. Some host bird can discover the eggs are not its own and throw these eggs away or abandons its nest and build a new nest in a new place. Some kind cuckoo birds can mimic the color and the pattern of the eggs of a few host birds in order to reduce the probability of discovering the intruding eggs. The cuckoos laid their eggs in a nest where the host bird just laid its own eggs, since the cuckoo eggs are hatching earlier than the host bird eggs. Once the eggs are hatching, the cuckoo chick's starts to propel the host eggs out the of the nest in order to increase its share of food provided by its host bird.

3.2 Levy flights random walks

Recent studies show that the behavior of many animals when searching for foods have the typical characteristics of Levy flights [13]. Levy flights is a random walk in which the step-lengths are distributed according to a heavy-tailed probability distribution. After many steps, the distance from the origin of the random walk tends to a stable distribution.

Algorithm 1 Cuckoo search algorithm

Set the initial value of the host nest size N,probability $p_a \in [0,1]$ *and* max*imum numberof iterations* Max_{itr}.
Set $t := 0$. *{Counter initialization}*.
for $(i = 1 : i < N)$ *do*
  Generate initial population of N host x_i^t. *{N is the population size}*.
  Evaluate the fitness function $f(x_i^t)$
end for
repeat
  Generate a new solution (Cuckoo) x_i^{t+1} *randomly by Levy flight.*
  Evaluate the fitness function of a solution x_i^{t+1} $f(x_i^{t+1})$
  Choose a nest x_j *among N solutions randomly.*
  if $(f(x_i^{t+1}) > f(x_j^t))$ then
   Re*place the solution* x_j^{t+1} *with the solution* x_i^{t+1}
  end if
  Abandon a fraction p_a *of worse nests.*
  *Build new nests at new locations u*sin *g Levy fight a fraction* p_a *of worse nests*
  Keep the best solutions (nests with quality solutions)
  Rank the solutions and nd the current best solution
  Set $t = t + 1$. *{Iteration counter increa*sin *g}*.
until $(t < Max_{itr})$. *{Ter*min *ation criteria satisfied}*.
Pr*oduce the best solution.*

4. Cross-scale Matching Pursuit (CMP)

Assume that we have a multi-scale dictionary $\{A_l | l = 1,...L\}$, the Cross-scale Matching Pursuit (CMP) algorithm aims to find the sparse coding coefficients for a signal of interest. Let α_i^l be the sparse coding coefficient vector for the signal x_i^l over the dictionary A_l. Orthogonal matching pursuit (OMP) [14] is applied to calculate sparse vectors within each single scale. Let N_l be the dimensionality of x_i^l. The average pixel representation error $\hat{\varepsilon}_i^l$ can be calculated as:

$$\hat{\varepsilon}_i^l = \|x_i^l - A_l \alpha_i^l\|_2^2 / N_l \tag{3}$$

For the group of signal vectors with the same index ibut from different scales $\{x_i^l \mid l = 1,...L\}$, one scale l_0 will be chosen if the dictionary atoms in A_{l_0} better represent the signal. The criterion for the selection is defined as:

$$l_0 = \arg\min_l \{\hat{\varepsilon}_i^l f(\|\alpha_i^l\|_0)\} \tag{4}$$

where $\|\alpha_i^l\|_0$ calculates the number of non-zero coefficients in α_i^l, and f (t) is a kernel function positively proportional to parameter t. In our current implementation, $f(t) = \sqrt{t}$.

The criterion in Eqn. (4) takes two factors into account during scale selection. The first factor is the representation error: for a fair comparison across scales, the vector error is divided by the its dimensionality, which measures the average pixel error. The second factor is the representation sparsity: measured in the 0 norm (number of non-zero coefficients) of the coefficient. The two factors ensure the fidelity and sparsity of a representation, which are the key concerns of the CMP [15]. The steps of the CMP algorithm are generalized in Algorithm 2.

5. Image denoising based on MSDL-CS algorithm

In this section, we introduce our MSDL-CS algorithm, which uses the multi-scale dictionary learning and cuckoo search algorithm for image denoising. Firstly, we decompose the observed image into patches with different scales. Secondly, we learn the dictionary by using the MSDL-CS algorithm, which uses the multiscale approach to get best sparsest atoms and the cuckoo search algorithm to update the dictionary. The MSDL-CS algorithmal ternate between getting the sparse representation of the image while fixing the dictionary and updating the dictionary whilefixing the representation to get the best dictionary to represent the important component in the image. Finally, the source image is reconstructed by using the learned dictionary and the sparse coding.

The main steps of the algorithm are:

• Sparse Coding Step: This is performed with Cross-scale Matching Pursuit.

• Dictionary Update: In the updating step we used the cuckoo search algorithm.

• Reconstruction: The last step is reconstructing the source image based on the learned dictionary and the sparse coding results.

Algorithm 2: MSDL-CS

Input parameter: input image I; multi scale dictionary $\{A_l \mid l = 1,..., L\}$; target coding error $\hat{\varepsilon}_0$.

-Decompose I into patches of different scales, and form into vectors: $\{x_i^l \mid i = 1,...; l = 1,...L\}$

for *each image patch* $i = 1,...$ *do*

for *each dictionary scale* $l = 1,..., L$ do

$-$*Set* initial support for x_i^l as $S_i^l = \Phi$; set initial residual: $\hat{\varepsilon}_i^l = \|x_i^l\|_2^2 / N_l$

while $\hat{\varepsilon}_i^l > \hat{\varepsilon}_0$ do

- Sweep current residual through all atoms in A_l. find the atom $d_{k_0}^l$ that produces the largest projection : $k_0 = \arg \max_k \{a_k^{lT} \hat{\varepsilon}_i^l\}$
- Update support $S_i^l = S_i^l \cup a_{k_0}^l$.
- Calculate coefficient s.t. $Supp\{\alpha_i^l\} = S_i^l$

$\alpha_i^l = \arg \min_\alpha \|x_i^l - A\alpha_i^l\|_2^2 / N_l$

- Update current residual according to :

$\hat{\varepsilon}_i^l = \|x_i^l - A\alpha_i^l\|_2^2 / N_l$

end

end

Dictionary update: update the dictionary atoms while fixing the data matrix and the sparse representation α by using the CS algorithm (Algorithm 1).

Reconstruction: reconstruct the denoised image $I_d = A\hat{\alpha}$

End

6. Experiments and Results

The performance of the proposed algorithm is tested with a real image data set. In this work, we used patches of different scales of the observed noise contaminated image as an initial dictionary. Each patch is arranged as an atom in the dictionary. The dictionary was learned by alternating between sparse coding with the currant dictionary and dictionary update with the current sparse representation. For doing that, we use the MSDL-CS algorithm. We applied the algorithm to Barbra image, and Castle image from Berkeley dataset). The proposed algorithm compared with two of the main image denoising techniques K-SVD, and SR based N-NMF which uses dictionary learning based algorithm. For quantitative comparisons, the reconstructed performs are measured in terms of Peak Signal to Noise Ratio (PSNR).

The results showed that using MSDL-CS algorithm gave a better result than K-SVD and SR-NNMF, specially with low level noise energy.

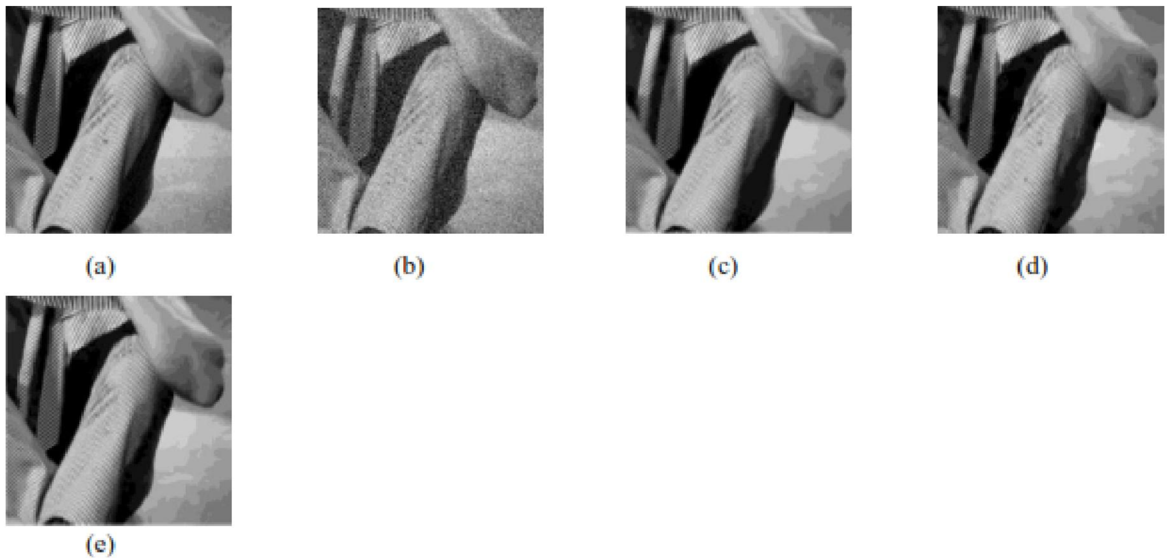

Fig. 1. (a) The original image. (b) The noised image by adding Gaussian noise with sigma=20. (c) denoised by K-SVD and (d) denoised by using SR-NNMF, (e) denoised by using MSDL-CS.

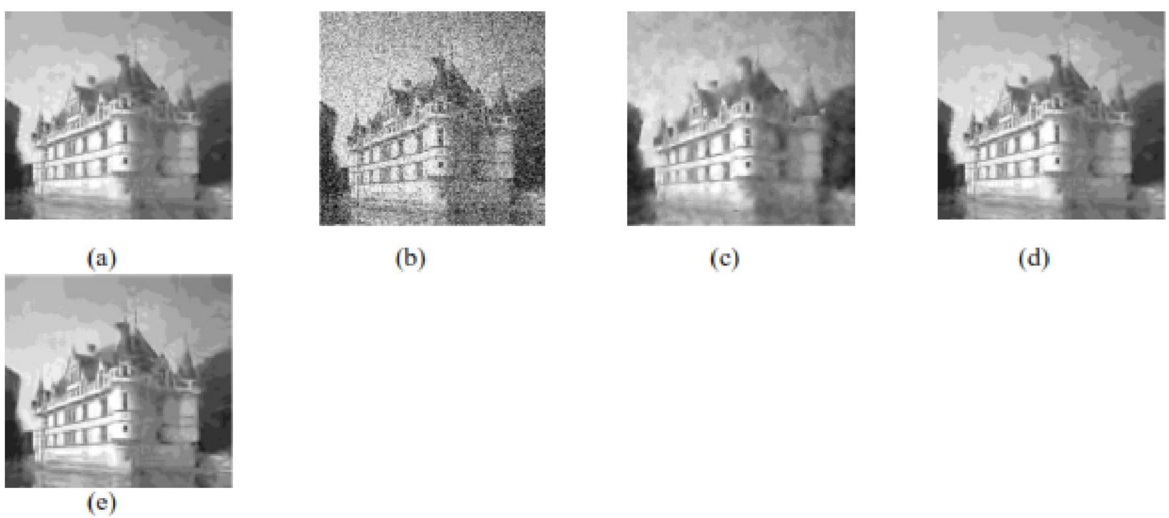

Fig. 2. (a) The original image. (b) The noised image by adding Gaussian noise with sigma=20. (c) denoised by K-SVD and (d) denoised by using SR-NNMF, (e) denoised by using MSDL-CS.

Table 1. The PSNR computed for 2 images with different noise variance level (sigma).

Sigma	Castle			Barbra		
	KSVD	SR-NNMF	MSDL-CS	KSVD	SR-NNMF	MSDL-CS
10	35.4574	38.5428	39.5519	33.3948	37.0749	39.254
15	32.1002	35.1285	35.4735	31.1033	32.6425	34.6584
25	31.1205	31.8820	33.5927	28.4547	28.8607	28.9628
30	27.2468	27.6652	27.9593	27.2819	27.5758	28.3281

7. Discussion and Conclusion

In this paper, we address the image denoising problem based on sparse coding over multi-scale over complete dictionary and cuckoo search algorithm. The obtained dictionary was been used to get a sparse coding for noised images, shows that it can capture the main component of the image. Experimental results show satisfactory recovering of the source image. Future theoretical work on the general behavior of this algorithm is on our further research agenda.

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