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Sparse Representation Based Single Image Dictionary Construction For Image Super Resolution

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ABSTRACT

Sparse representation- linear combination of very few elements which are represented in vector format called as atoms. Dictionary- specific data set is formed to reconstruct the signal. Generally dictionary can be trained in two ways (i) Based on sparse mathematical model (ii) learning a dictionary based on training set or external images. In this paper a new Super Resolution (SR) approach is employed for underwater side scan sonar image. The SR technique exploits dictionary based sparse representation model. In order to extemporaneously construct an over-complete dictionary from a single image a new algorithm is proposed. Proposed approach improves performance through joint combinatorial optimization of sparse coefficients and Dictionary. In proposed super resolution technique efficiency is measured using various performance metrics like peak signal to noise ratio (PSNR) and structural similarity index measurement (SSIM). Proposed technique of super resolution further reduces the computational time.

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INTRODUCTION

In the field of image processing, super resolution is one of the most developing area. In order to obtain an image with good quality, super resolution is used. For past few decades many algorithm and techniques were developed to perform super resolution. Super resolution is used to enhance the details from given image. Super resolution is a technique which is used for viewing an image in detailed manner, for the requirement of information. Many SR algorithms have been developed for natural images. These algorithms can be implemented for underwater side scan sonar images. Nowadays side scan sonar images place a vital role in science and navy field. It is mainly used in seafloor for dredging operations, fisheries reaches and maritime archaeology. Military field uses sonar images for finding H-bomb and submarines. In order to obtain information from side scan sonar image a new super-resolution algorithm is proposed in this paper. When low resolution sonar image is taken for observation, object in the image cannot be viewed accurately. In order to view them in a proper way super resolution is required. Super resolution techniques can be implemented by increasing the resolution of imaging devices or applying super resolution algorithms. First method tends to be costly and it is not be feasible for all users, so second method of SR is considered. In this, two main categories of algorithm are there (I) example based and (II) classical based.

In classical method, multiple frames of low frequency images of same scene are combined to form a single image which is the resulting super-resolution image. This method of super-resolution is too costly to be executed. In example based technique the super-resolution image is obtained by, learning the relationship between low frequency and high frequency image patches for same input image. Several algorithms are developed to perform image super resolution. In recent years exampled based algorithm is executed with dictionary and sparse representation. Sparse representation is a latest technique used in image processing. Sparse representation is a linear combination of elements called atoms. In this method the number of non-zeros entities will be very less, in the obtained sparsity coefficient. . For finding sparse coefficient several algorithm has been proposed. Sparse coefficient can be formed by using Matching Pursuit (MP), Orthogonal Matching Pursuit (OMP) in (Pati, Y.C., 1993), Order Recursive Matching Pursuit (ORMP),

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Basis Pursuit (BP) (Mairal, J., 2009; Engan, K., 1998; Engan, K., 1999; Skretting, K. and K. Engan, 2010; Yaghoobi, M., 2009). Matching Pursuit type sparse approximation finds the best matching of data. Basic Pursuit will decompose a signal into optimal solution. In this sparsity and super resolution will be better compared to MP. Orthogonal Matching Pursuit is an iterative greedy algorithm which takes a single column for each step and it will be correlated with current residuals.

Dictionary is a set of data, which is used to reconstruct a signal. It is a vast field. Formation of dictionary can be done with several algorithms. In the past decade numerous algorithms for dictionary formation have been developed. Recursive Least Square (RLS) is a dictionary based algorithm, which will continuously update the training vector during processing (Skretting, K. and K. Engan, 2010). Method of Optimized Directions (MOD) in this method, selection of vector is done by frame design technique (Engan, K., 1999). Least Square Dictionary Learning algorithm (ILSDLA) is a dictionary learning algorithm proposed in (Engan, K., 2007).

Online Dictionary Learning (ODL) proposed in [4], for each iteration dictionary is updated. Each time ODL will generate a new dictionary. K-SVD is a dictionary learning algorithm for creating sparse representation (Aharon, M., 2006). K-SVD is a generalization of the k-means clustering method. Iteratively alternating between sparse coding the input data based on the obtained dictionary. Updating of the dictionary is done, until it is fit for the data.

1.1 Basicideas:

Dictionary D ℝ where K is called atoms. It is an over complete dictionary so (K > n). Signal is represented as *x*D where ℝ which has a very few number of nonzero entries. *x*is a high resolution patch. Low resolution image patch y = L*x*, where L is a projection matrix. High resolution image patch can be recovered from a low resolution patch, with the help of dictionary formation. In general (Elad, M. and M. Aharon, 2006; Mairal, J., 2008) proposed an algorithm to learn an overcomplete dictionary from natural images and implemented it for denoising problem. To generate a dictionary many algorithm are used. Dictionary is database which is a set of all data. According to the requirement, dictionary is chosen from the database. Learning of a dictionary is done with the help of K-SVD algorithm. Even with requirement of input, database can be formed by collecting same gender images. After completing the formation of dictionary, it is taken for sparse efficient. By having both reconstruction of image by using exampled algorithm is done. Our paper is organized as (II) Proposed Method, (III) Super resolution via Sparsity, (IV) Dictionary Learning, (V) Simulation result.

1.2 Notations:

X and Y denotes high resolution and low resolution image, x and y are corresponding image patches. HR for high resolution and LR for low resolution D for dictionary, D_h and D_l are dictionary from High resolution image patches and Low resolution image patches respectively. α is the sparse coefficient.

2 Proposed method:

In our proposed method, instead of a single dictionary, couple dictionary is used. K-SVD is used for training the dictionary. D_h for high resolution image patch and D_l for low resolution image patch. D_l used to recover their respective D_h image patches. These two dictionary are formed to reconstruct an image. Image patches are formed by overlapped fashion. The overlapped of patches follows one pixel overlapped fashion. Each patches are concatenated through proper normalization method. This is done to enforce that both D_h and D_l patch pair should have the same sparse representation. Sparse coefficient is formed by OMP function. By making one fixed other is updated and vice versa. This will be discussed in future.

3 Dictionary Learning:

A signal can be represented as $D\alpha$ where D is an over complete dictionary. As discussed earlier dictionary is formed from blocks, which is given as input. The block are further divided into several image patches. With the help of these patches dictionary is formed. Learning a dictionary is dictionary is done by (i) keeping D fixed, α is updated (ii) α is fixed, D is updated. Dictionary is learned from training set. Common trained set of data are available. In our proposed method data set is trained by Online Dictionary Learning. Let training be X = { $x_1, x_2, \ldots, x_n$ }. It is hard to learn dictionary to have sparse representation of *y*, it can be recovered from norm-minimization (ℓ_1).

$$D = \arg\min_{D,\alpha} \| X - D\alpha \|_2^2 + \lambda \| \alpha \|_1$$

$$\text{s.t.} \| D_i \|_2^2 \leq 1, i = 1,2,\ldots,K \qquad (1)$$

where the ℓ_1 norm $\|\alpha\|_1$ is to enforce sparsity, and the ℓ_2 norm is to remove scaling ambiguity.

The optimization is done by the learning method:

1) D has to be initialized with Gaussian random matrix, and each column is unit normalized.

2) D is fixed, α is updated.

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$$\alpha = \arg\min_{\alpha} \| X - D\alpha \|_2^2 + \lambda \| Z \|_1 \quad (2)$$

This can be solved efficiently

3) α is fixed, D is updated.

$$D = \arg\min_{D} \| X - D\alpha \|_2^2$$

$$\text{s.t.} \|D_i\|_2^2 \leq 1, i = 1,2,\ldots,K \quad (3)$$

4) Iteration will be continued until it get converged.

Since our proposed algorithm use joint dictionary. Training of couple dictionary is done with help of image patch pair. R $=\{X^h, Y^l\}$, where $X^h = \{x_1, x_2 \ldots x_m\}$ sampled HR image patches and $Y^l = \{y_1, y_2, \ldots y_m\}$ these are corresponding LR image patches. To learn a dictionary for HR and LR image patches, so that the sparse representation should be same. Instead of finding D_h and D_l separately, it can be combined together so that it can have same sparse representation.

$$D_h = \arg\min_{\{D_h, Z\}} \left\| X^h - D_h\alpha \right\|_2^2 + \lambda \| Z \|_1 \quad (4)$$

and

$$D_l = \arg\min_{\{D_l, \alpha\}} \left\| Y^l - D_l\alpha \right\|_2^2 + \lambda \| Z \|_1 \quad (5)$$

Now these equation is combined to form

$$\min_{\{D_h, D_l, \alpha\}} \frac{1}{N} \| X^h - D_h\alpha \|_2^2 + \frac{1}{M} \left\| T^l - D_l\alpha \right\|_2^2 + \lambda \left(\frac{1}{N} + \frac{1}{M} \right) \|\alpha\|_1 \quad (6)$$

Feature representation for LR image patch is done to ensure that the coefficient are relevant and have more prediction to reconstruct a HR image. As always HR image patches has information in LR image, high-pass filter is used to extract it. In order to boost the prediction accuracy Freeman *et al*. (2000) used to extract edges from low-resolution image. Sun *et al*. (2003) to extract contours Gaussian derivative filter is used. To represent patches first and second-order gradients is used in Chang *et al*. (2004). In our paper, to extract features first-order and second-order derivatives is employed, because it is very simple and effective.

$$f_1 = [-1 \quad 0 \quad 1], \quad f_2 = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

$$f_3 = [1 \quad 0 \quad -2 \quad 0 \quad 1] \quad f_4 = \begin{bmatrix} 1 \\ 0 \\ -2 \\ 0 \\ 1 \end{bmatrix}$$

When it is applied four different features are formed for four filter and then these are concatenated to form a single vector. But in our paper these filters are applied to training images, so that we get four gradient maps and from the four patches were extracted. Now concatenate them to form a single feature vector. Therefore, feature representation is done for each low resolution image. But in practice, to extract a better features, upsampled image of low resolution image is employed. Upsample is done using Bicubic interpolation. Now feature is extracted, with the help of this low resolution image patches are taken.

4 Super Resolution via Sparasity:

Obtaining super resolution image from a low resolution image works as an ill-posed problem. Super resolution problem is employed by (1) reconstruction constraint and (2) sparsity prior. Reconstruction constraint technique is used to obtain required high resolution image *X* from given low resolution image *Y*. Sparsity prior is a low resolution image patch can be sparsified and it can be represented in sparse representation with the help of over complete dictionary, this will give high resolution image patches.

Reconstruction constraint is obtained by adding a blurring factor and downsampling the HR image. The HR image is given as input to blurring filter and down sampling operator. This was proposed by Yang *et al*.

$$Y = SHX \quad (7)$$

Where *S* down sampling operator and *H* is a blurring filter Sparsity prior are HR image patches, which is represented as x . *X* can be represented as a linear combination of atoms in a dictionary D_h from a high resolution sampled patches. $x \approx D_h\alpha$ .Yang *et al*. sparse representation is done by using local model and reconstruction constraint is done using global model. The dictionary obtained is used to find sparse coefficient by using OMP function. With this sparse coefficient fixed dictionary is updated. Obtained dictionary will have required data than the initial dictionary. By taking updated dictionary sparse coefficient is updated.

Table 1: PSNR (dB) (Peak Signal to Noise Ratio).

Images	bi-cubic	Yang	Proposed
Sand Ripples	22.866	22.776	25.389
L3 Klein wreck	29.671	29.229	39.704
Navy PB4Y-2 Privateer	31.571	31.285	33.722
Sunken Car	28.689	28.482	39.248

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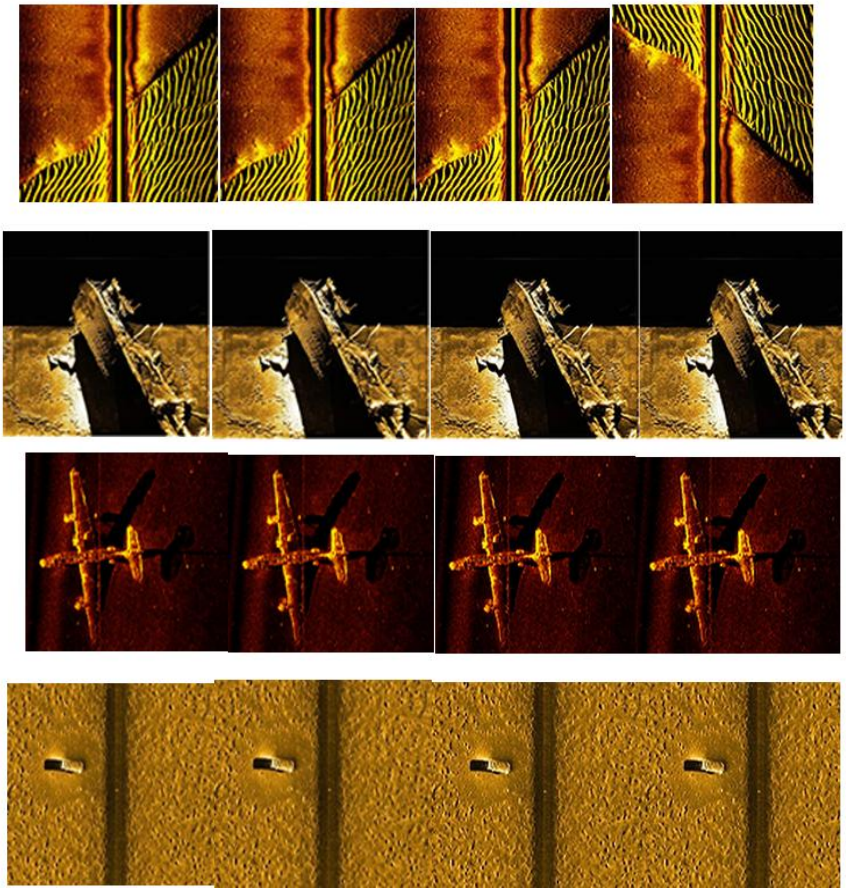
Table 2: RMSE (Root Mean Square Error).

Images	bi-cubic	Yang	Proposed
Sand Ripples	18.3322	18.525	13.710
L3 Klein wreck	8.374	8.811	7.638
Navy PB4Y-2 Privateer	6.729	6.954	5.252
Sunken Car	9.376	9.603	8.780

Table 3: SSIM (Structural Similarity Index Measurement).

Images	bi-cubic	Yang	Proposed
Sand Ripples	0.9933	0.9922	0.9917
L3 Klein wreck	0.9913	0.9798	0.9820
Navy PB4Y-2 Privateer	0.9909	0.9795	0.9558
Sunken Car	0.9788	0.9989	0.9988



Input LR image Bicubic image Yang et al. [17] Proposed method

Fig. 1: Experimental results obtained using proposed and other SR algorithms on side scan sonar images.

6 Result:

The proposed algorithm for single image super resolution is used to super resolve the side scan sonar images. Thereby the quality of the existing sonar images is enhanced providing visually good images. The obtained results of the proposed algorithm are compared with the outcomes of some recently evolved SR algorithms like bi-cubic technique and Yang *et al*. method. The comparison is done using their open source implementation.

The resultant SR images are magnified by a factor of 2X. The LR and HR dictionaries are learned using a single image as input. The patch size is chosen to be a=3 in all the experiments. The value of regularization parameter is chosen as 0.15. The number of atoms in the dictionary is fixed as k=512 atoms.

The proposed SR algorithm was applied to various underwater images. Results obtained using the proposed method and other techniques are shown in Fig.1. From Fig.1 it can be seen that the proposed algorithm produces visually appealing images.

In order to measure the performance of the proposed method various metrics are evaluated. Peak signal to noise ratio (PSNR), Root mean square error (RMSE) and Structural similarity index measurement (SSIM) values are determined for the resulting images so as to check their quality.

Table.1 summarizes the PSNR values obtained for all methods. The RMSE and SSIM values are

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tabulated in Table.2 and Table.3 respectively. From the obtained values proposed method has better result than the existing method. This method is used for both natural and side scan sonar image.

Table.1 summarizes the PSNR values obtained for all methods. The RMSE and SSIM values are tabulated in Table.2 and Table.3 respectively. From the obtained values, we show that the proposed produces better results than the existing methods. This method of single image SR can be used for both natural images and side scan sonar images.

7 Conclusion:

This paper presents a new SR approach for single side scan sonar image based on sparse representation. The proposed SR technique involves the formation of a sparse dictionary. The HR result is obtained by sparse representation of input image using the dictionary. The dictionary learning phase involves the construction of LR and HR dictionaries from the LR and HR image patches respectively. The obtained dictionaries are jointly trained. The trained dictionaries help in efficient reconstruction of the SR image. Experimental result shows outcome of the proposed algorithm, for side scan sonar images. Resulted values of PSNR, SSIM and RMSE has been improved for side scan.

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