Quaternion Matrix Approach for Color Image with Vector Sparse Representation

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Abstract*- Conventional sparse image models treat image pixel as a scalar, which represents color channels separately or concatenate color channels as indefinite image. In this paper, we propose a vector sparse representation model for color images using quaternion matrix approach. As a new tool for color image representation, it is a possible applications in a number of image-processing tasks are presented, including color image resolution-up, resolution-down, reconstruction, denoising, and inpainting. The proposed system represents the color image as a quaternion matrix, where a quaternion-based dictionary learning algorithm is existing using the K-quaternion singular value decomposition (QSVD) (generalized K-means clustering for QSVD) method. It conducts the sparse origin selection in quaternion space, which uniformly transforms the channel image to an orthogonal color space. In this new color space, it is important that the inherent color structures can be entirely preserved during vector reconstruction. Additionally, the proposed sparse model is more efficient compare with the current sparse models for image restoration tasks due to poorer redundancy between the atoms of different color channels. The new outcome show that the proposed sparse image model avoids the hue bias issue successfully and shows its potential as a common and powerful tool in colored image analysis and processing domain.*

Keywords- Vector sparse representation model, quaternion matrix analysis model, color image, dictionary learning, K-QSVD, image restoration.

I. INTRODUCTION

It is easy and designed to be a truly direct generalization of the k-means. As such, when enforced to work with one atom per signal, it train a dictionary for the gain-shape VQ. When forced to have a part coefficient for this atom, it exactly make a replica the K-means algorithm. The K-SVD is very efficient, due to an effective sparse coding and a Gauss–Seidel like accelerate dictionary update method. Sparse coding that is, model data vectors as sparse linear combinations of fundamental elements. It is broadly used in signal processing, neuroscience, and statistics [2]. In dictionary adapt specific data, to be very effective for signal restoration and classification in the audio and image processing. A proof of convergence is presented, along by experiments with natural images representing that it leads to more rapidly performance and enhanced dictionaries than traditional batch algorithms for both small and large datasets. It is flexible and works in conjunction with any pursuit algorithm.

The algorithm’s steps are coherent with each one other, both work towards the minimization of a clear taken as a whole objective function [3]. Sparse coding provide a class of algorithms for finding brief representations of stimuli; given only unlabeled input data, it learns base functions that capture high-level features in the data. When a sparse coding algorithm is apply to natural images, the learned bases equal to the receptive fields of neurons in the visual cortex [4]. Compared with conventional OMP and K-SVD, the future QOMP and K-QSVD algorithms have higher computational complexity.

Sparse representation has been widely used for image classification. Sparse representation achieves impressive results on face recognition. The full training set is taken as the dictionary. Denoising is implemented class by class, which gives rise to tremendous computational cost as class number increases. [5] Enhances a sparse coding dictionary’s discriminate ability by learn a low-rank sub-dictionary for each class. This process is time-consuming and might increase the redundancy in each sub-dictionary, thus not guaranteeing consistency of sparse codes for signals from the same class. Sparse demonstration base categorization has led to exciting image identification results, while the dictionary used for sparse coding plays a key role in it.[7] new scalable and highly flexible color image coder based on a similar Pursuit increase. Difficulty of learning dictionaries for color Images and make longer the K-SVD-based grayscale image denoising algorithm [8] A set of training shapes of many object classes, a sparse linear combination of training shapes in a low dimensional illustration is used to regularize the target shape in variation image segmentation.

By minimizing the proposed variation functional, the model is capable to automatically select the reference shapes that best represent the object by sparse recovery and correctly fragment the image, taking into account both the image information and the shape priors. For some applications under a suitable range of training set, the proposed Matching Pursuit algorithm provides a basically progressive stream and the planned coder allows us to rebuild color information from the first bit received. In order to powerfully capture edges in usual image, the dictionary of atoms is build by translation; rotation and anisotropic refinement of a wavelet-like protect function. This dictionary is also invariant under shifts and isotropic scaling, thus leading to very easy spatial resizing operations. This flexibility and adaptively of the MP coder makes it appropriate for asymmetric applications with heterogeneous end user terminals.[7] The image denoising problem, where zero-mean white and homogeneous Gaussian additive noise is to be removed from a known image. The approach taken is based on sparse and redundant representations over trained dictionaries. With the K-SVD algorithm, we achieve a dictionary that describes the image content in actual fact. Two training options are consider: use the corrupted image, or training on a corpus of high-quality image database. Since the K-SVD is restricted in handling small image patches, we extend its deployment to arbitrary image sizes by defining a worldwide image prior that forces scarcity over patches in all location in the image. We show how such Bayesian treatment leads to an easy and effective denoising algorithm. The set model allows artificial enlargement of the training set by include a definite number of transformed shapes for transformation invariance, and then the model remains jointly convex and can handle the case of overlap or many objects presented in an image within a small range. Numerical experiments show promising results and the likely of the method for object classification and segmentation. [9] Super-resolution (SR) image reconstruction is now a very active area of research, as it offers the promise of overcome some of the original resolution limitations of low-cost imaging sensors [10].

II. SCOPE

A. Scope of the system

a. To remove the disturbances (noise) using K-QSVD algorithm.
b. Increase or decrease the resolution of the input image.
c. Zoom-in or zoom-out of input image.
d. Finding the four quarter.
e. Get output as gray scale image.

III. SYSTEM ARCHITECTURE

A. Architecture Flow

All the images are stored in the Image System. The user initially browses image files from the image system. The images are of the extensions (jpg or pang or gif). User then passes the browsed image to Image Quaternion System. Image Quaternion System generates Dictionary Training Set Data on the image. Image Quaternion System generates vector representation of the pixel matrix of the image. It then scans whether the vector matrix generated is sparse. (Sparse is a matrix in which most of the element are zero).

Image Quaternion System has following features based on

Vector Sparse Matrix:

1. Denoised Image-In this feature we remove all the noises or disturbances in the image.
2. Feature Extraction-In this feature we extract or separate regions based on color codes present in the image.
3. Resolution-We increase celerity of the image either by increasing or decreasing resolution of the image.

Finally after performing all the features, we get Reconstructed Image which is better and clear image using Image Quaternion System based on Vector Sparse Matrix.

B. Image Quaternion System Architecture

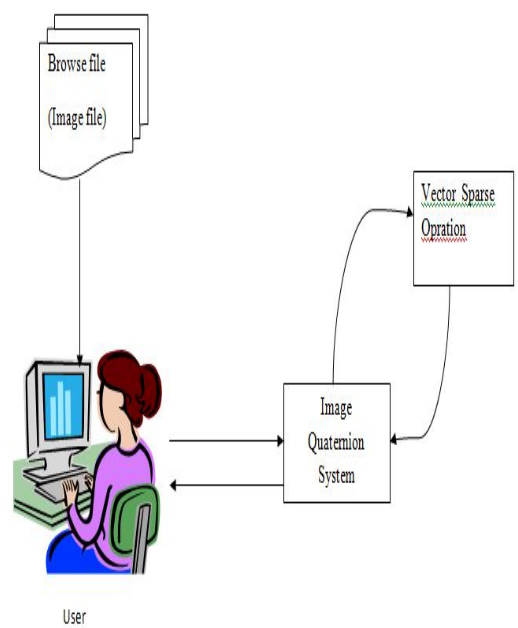


Figure: Image Quaternion System Architecture

IV. APPLICATION

A. Color Image Reconstruction

We first paragon the proposed sparse model with the model in (24) for color image reconstruction. The dataset for training consists of 40,000 image sample patches of size 8×8, which are randomly selected from a wide variety of animal images with separate scenes. Some of them are shown in Fig. 1. Then we train the dictionaries using K-SVD and K-QSVD separately on the same training samples.

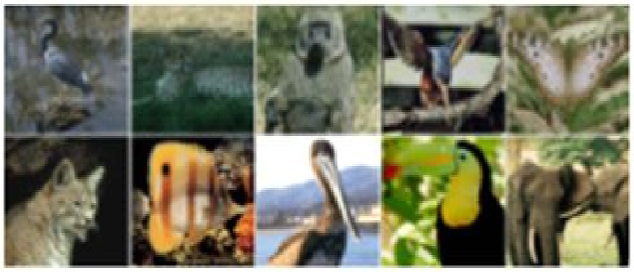


Figure 4.1: Examples of training images for color image reconstruction.

B. Color Image Denoising

Color Image denoising problem, where zero-mean white and homogeneous Gaussian additive noise is to be removed from a given image. The treat taken is based on sparse and redundant representations over trained dictionaries. Using the K-SVD algorithm, we gain a dictionary that describes the image accessories effectively. Two training options are considered: First is using the corrupted image itself, or second is training on a corpus of high-quality image database. Since the K-SVD is restricted in handling small image patches, we extend its deployment to arbitrary image sizes by defining a global image previously that forces scarcity over patches in each location in the image. Image denoising is an intrinsic image processing task, all as a process itself, and as a component in another processes. Very ways to denoise an image or a set of data exists. The main property of a good image denoising model is that it will remove noise while preserving edges. Conventional, linear models have been used. One common approach is to use a Gaussian filter or same like solving the heat equation with the noisy image as input data. For some purposes this kind of denoising is adequate. One important advantage of linear noise removal models is the speed. But a back draw of the linear models is that they are unable to preserve edges in a good manner: edges, which are recognized as discontinuities in the image, are blur out. Nonlinear models on the other hand can handle edges in a much better way than linear models can. Total Variation (TV) filter is much better at preserving edges, but smoothly varying regions in the input image are transformed into piecewise stationary regions in the output image. Using the TV-filter as a denoiser leads to solving a second order nonlinear PDE. From this smooth regions are transformed into piecewise constant regions when using the TV-filter, it is desirable to prepare a model for which smoothly varying regions are transformed into smoothly varying regions, and yet the edges are preserved.

Figure 4.2: Columns from left to right: Original image, noisy image, improved K-SVD and proposed K-QSVD denoising results.

C .Color Image Inpainting

Color Image inpainting context to filling the missing information in an image. Limited by the patch size, the learning based method can only handle little holes. In this paper, focus on filling missing areas within the order of 30 pixels. We randomly choose a full image which is damaged by randomly deleting a fraction r of the pixels.

a. In this we only consider the projections of without corrupted pixels onto dictionary in the Quaternion Orthogonal Matching Pursuit.
b. The coefficient vector for every patch p can be approximated only on the non-corrupted pixels using the pruned dictionary by selecting corresponding rows.
c. The computed coefficient vector can be shared with those missing pixels, consulting its validity for the complete patch block p. Hence, the reconstructed block x is obtained as x= ˙ D˙ ap.

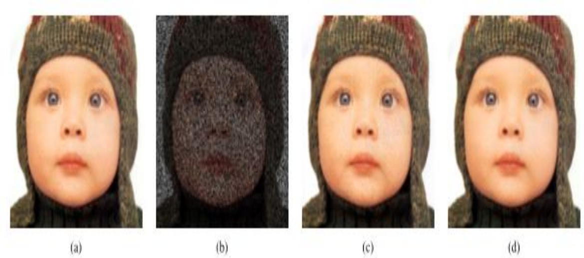


Figure 4.3: Visual comparisons and PSNR(dB) results of K-SVD method and the quaternion-based sparse model on image inpainting. (a) Ground truth. (b) Damage (c) K-SVD (d) K-QSVD

D. Single Color Image Super Resolution

This application refers to the process of obtaining higher resolution (HR) images XH from a lower- resolution (LR) image XL. Agoing image super resolution methods can be divided into three categories: interpolation based methods; reconstruction based methods and third is example based methods. Among interpolation based algorithms, first one bi-linear and second one bi-cubic are most commonly used but tend to produce blurry and jaggy artifacts. Reconstruction-based methods require the stability of up-sampled image with the input LR image, where the HR-to-LR degradation process is reversed by many kinds of edge prior models. More recent researches have focused on the third type, i.e., example based methods, which reorganize the high- frequency band of LR image using the provided example database.

Figure 4.4: 3X super-resolution results of birds with PSNR (dB) and SSIM. (a) Input. (b) Bi-cubic (c) Shan (d) Yang (e) Zeyede (f) OnlineQ (g) Proposed

V. ALGORITHM

Algorithm for Quaternion K-SVD (QK-SVD):

Input: $Y \in \mathbb{H}^{n \times k}$ Quaternion matrix of sample vectors,

ε **Q-OMP** threshold,

J number of iterations,

$D_0 \in \mathbb{R}^{n \times m}$ initial Quaternion dictionary with normalized columns

1. $D \leftarrow D_0$
2. For $j = 1 \ldots J$ do:

3.1 **sparse coding**

3.1.1 For each column Y_i of Y do:

3.1.1.1 Solve $\min_{x_i \in \mathbb{R}^m} \|x_i\|_0 \quad s.t. \quad \|Y_i - Dx_i\|_2^2 \leq \varepsilon$ via **Q-OMP**

3.2 **dictionary update**

Let $X = [x_1 | \ldots | x_k]$.

3.2.1 For each atom d_{j_0} of D do:

3.2.1.1 $\Omega_{j_0} = \{ i \mid X_{j_0 i} \neq 0 \}$

3.2.1.2 $E_{j_0} \leftarrow Y - \sum_{\substack{j=1 \\ j \neq j_0}}^{k} d_j X_j^T$

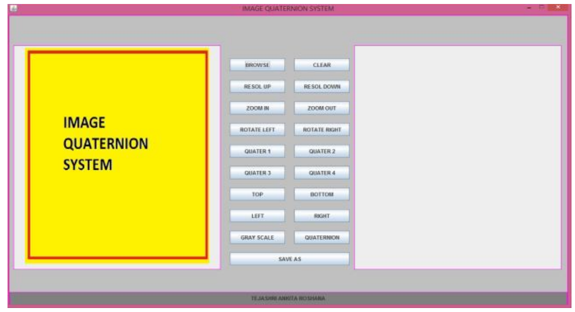
3.2.1.3 Restrict E_{j0} by choosing only the columns corresponding to Ω_{j_0}

3.2.1.4 Let $E_{j_0} = U \Sigma V^*$ be the Quaternion singular-value decomposition (SVD) of E_{j_0}. Then: $d_{j_0} \leftarrow u_1, X_{j_0, \Omega_{j_0}} \leftarrow \sigma_1 \cdot v_1^*$

VI. RESULT

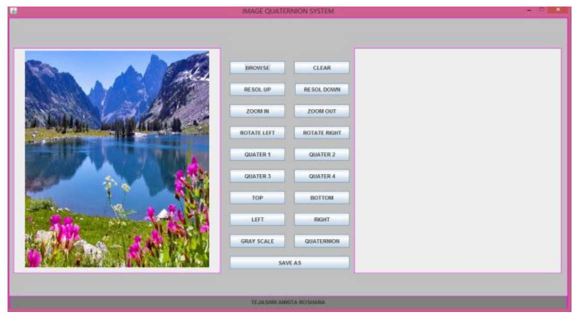
Step 1: Front Page

Front page contains two panels where one is for load input image and second where output image is displayed.



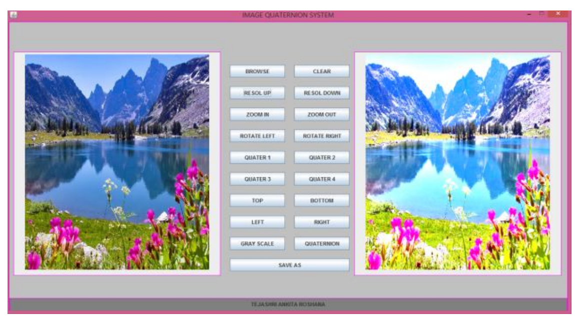
Step 2: Browse Image

On the output window image is loaded for performing different operations on that loaded image.



Step 3: Resolution Up

We can perform resolution-up operation on loaded image.



Step 4: Resolution Down

We can perform resolution-down operation on loaded image.

Step 5: Gray Scale

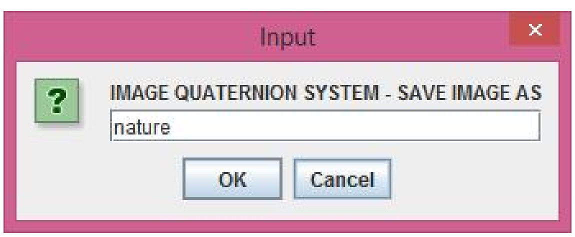
We can perform grayscale operation on loaded image.

Step 6: Quaternion Effect

We can perform quaternion operation on input image and we get output as better image.

Step 7: Save as

Using this button we can save the output image.



VII. CONCLUSION

In this project, we propose a vector sparse model for color image using quaternion matrix analysis. It formulate a color pixel as a vector unit as an alternative of a scalar quantity and as a result overcomes the lack of accuracy describing interrelationship among color channels. Many problems are reduces such as reconstruction, denoising, inpainting, and super-resolution on natural color images. We will additional survey the potential extension of quaternion sparse model to four channel color space, in which the real part may correspond to the black channel. Additionally, from the view of algorithm our K-QSVD algorithm does not assurance global convergence. in recent times, a dictionary learning algorithm based on proximal method is future which achieves global convergence. Inspired by this strategy, we plan to more improve our learning algorithm in the future work.

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