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Vector Sparse Representation of Color Image Using Quaternion Matrix Analysis based on Genetic Algorithm

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Abstract *- Vector sparse image models use color image pixel as a scalar vector, that represents color channels independently or concatenate color channels as an indefinite image. In this paper, we recommend a vector sparse representation model for color images using quaternion matrix scrutiny and Genetic algorithm for reduce distortion. 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 system based on Genetic Algorithm. Genetic Algorithms (GAs) are adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics. Sparse representations have been extended to deal with color images composed of three channels. 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. In this model, spatial morphologies of color images are encoded by atoms, and colors are encoded by color filters. By the use of Genetic algorithm, we remove the distortion from image.*

Keywords *- Vector Sparse Representation, Quaternion Matrix Analysis, Color Image, Genetic Algorithm (GA), K-QSVD, image restoration.*

1. 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 trains 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 [1]. 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 with 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 [2]. 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 [3]. 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. [4] 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. [5] New scalable and highly flexible color image coder based on a Matching Pursuit expansion. Difficulty of learning dictionaries for color images and makes longer the K-SVD-based gray scale image denoising algorithm. [7] 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 built 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.[6] 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 sparsity 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. [8] 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 [9].

In recent years, the learning based strategy for designing are proposed to represent input signals more sparsely. Structures low rank representation for signal classification has attracted much attention of researchers. Compact and discriminative dictionary is learned to include structure data information based on the result of a linear predict classifier. The new concept of block sparsity and group sparsity are defined to get more structural coefficient for different classes. There is a shortage of general model and technique for color image analysis and processing. This sparse model achieved the state-of-the-art performance on gray-scale images.

There are very few works on the sparse representation model of multichannel signals, which are typically presented as color images. The sparse models in have achieved the state-of-the-art performance on gray-scale images. As for color images, they just treat RGB channels as three independent “gray-scale” images and process them in a monochrome way. These works completely ignore the inter-relationship among the multiple channels, which is likely to produce distortions in the reconstruction results.

Genetic Algorithm (GA) An evolutionary algorithm which generates each individual from some encoded form known as a "chromosome" or "genome". Chromosomes are combined or mutated to breed new individuals. "Crossover", the kind of recombination of chromosomes found in sexual reproduction in nature, is often also used in GAs. Here, an offspring's chromosome is created by joining segments chosen alternately from each of two parent’s chromosomes which are of fixed length. GA is useful for multidimensional optimization problems in which the chromosome can encode the values for the different variables being optimized.

2. Genetic Algorithm

Genetic algorithm is a population-based search method. Genetic algorithms are acknowledged as good solvers for tough problems. However, no standard GA takes constraints into account. This chapter describes how genetic algorithms can be used for solving constraint satisfaction problems.

I. What is Genetic Algorithm?

The general scheme of a GA can be given as follows:

begin
INITIALIZE population with random candidate solutions;
EVALUATE each candidate;
repeat
SELECT parents;
RECOMBINE pairs of parents;
MUTATE the resulting children;
EVALUATE children;
SELECT individuals for the next generation
until TERMINATION-CONDITION is satisfied
end

The GA can be represented in form of a diagram:

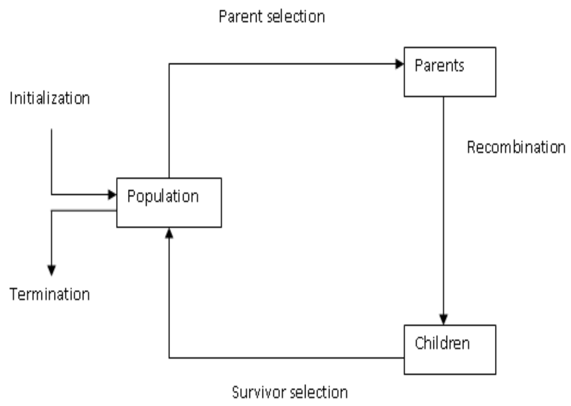

Figure 1 The general scheme of genetic algorithm

It's clear that this scheme falls in the category of generate-and-test algorithms. The evaluation function represents a heuristic estimation of solution quality and the search process is driven by the variation and the selection operator. GA has a number of features:

- GA is population-based
- GA uses recombination to mix information of candidate solutions into a new one.
- GA is stochastic.

II. Components of Genetic Algorithm

The most important components in a GA consist of:

- representation (definition of individuals)
- evaluation function (or fitness function)
- population
- parent selection mechanism
- variation operators (crossover and mutation)
- survivor selection mechanism (replacement)

Representation

Objects forming possible solution within original problem context are called phenotypes, their encoding, the individuals within the GA, are called genotypes. The representation step specifies the mapping from the phenotypes onto a set of genotypes. Candidate solution, phenotype and individual are used to denote points of the space of possible solutions. This space is called phenotype space. Chromosome and individual can be used for points in the genotype space. Elements of a chromosome are called genes. A value of a gene is called an allele.

Variation Operators

The role of variation operators is to create new individuals from old ones. Variation operators form the implementation of the elementary steps with the search space.

Mutation Operator

A unary variation operator is called mutation. It is applied to one genotype and delivers a modified mutant, the child or offspring of it. In general, mutation is supposed to cause a random unbiased change. Mutation has a theoretical role: it can guarantee that the space is connected.

Crossover Operator

A binary variation operator is called recombination or crossover. This operator merges information from two parent genotypes into one or two offspring genotypes. Similarly to mutation, crossover is a stochastic operator: the choice of what parts of each parent are combined, and the way these parts are combined, depends on random drawings. The principle behind crossover is simple: by mating two individuals with different but desirable features, we can produce an offspring which combines both of those features.

Parent Selection Mechanism

The role of parent selection (mating selection) is to distinguish among individuals based on their quality to allow the better individuals to become parents of the next generation. Parent selection is probabilistic. Thus, high quality individuals get a higher chance to become parents than those with low quality.

Survivor Selection Mechanism

The role of survivor selection is to distinguish among individuals based on their quality. In GA, the population size is (almost always) constant, thus a choice has to be made on which individuals will be allowed in the next generation. This decision is based on their fitness values, favoring those with higher quality.
As opposed to parent selection which is stochastic, survivor selection is often deterministic, for instance, ranking the unified multiset of parents and offspring and selecting the top segment (fitness biased), or selection only from the offspring (age-biased).

Initialization

Initialization is kept simple in most GA applications. Whether this step is worth the extra computational effort or not is very much depending on the application at hand.

Termination Condition

Notice that GA is stochastic and mostly there are no guarantees to reach an optimum.
Commonly used conditions for terminations are the following:

1. The maximally allowed CPU times elapses

2. The total number of fitness evaluations reaches a given limit
3. For a given period of time, the fitness improvement remains under a threshold value
4. The population diversity drops under a given threshold.

Note: Premature convergence is the well-known effect of losing population diversity too quickly and getting trapped in a local optimum.

Population

The role of the population is to hold possible solutions. A population is a multiset of genotypes. In almost all GA applications, the population size is constant, not changing during the evolutional search.

Performance Parameters

Input image is to be compressed to a certain level using DWT / FWT based lifting and quantization scheme explained above by maintaining a good signal to noise ratio. Quantitative analyses have been presented by measuring the values of attained Peak Signal to Noise Ratio and Compression Ratio at different decomposition levels. The intermediate image decomposition windows from various low pass and high pass filters.

PSNR:

Peak Signal to Noise ratio used to be a measure of image quality. The PSNR between two images having 8 bits per pixel or sample in terms of decibels (dBs) is given by:
PSNR = 10 log10xmean square error (MSE)

3. Previous Work

A common problem encountered in the quality of the images is the presence of noise. In recent years, there has been a great interest in the use of various classes of algorithms to enhance the quality of an image by removing noise.
G. HariPriya et al., February 2014 proposed that Noise Removal in Image Using LPG-PCA (Local Pixel Grouping Principle Component Analysis) Algorithm. In this, an effective algorithm for noise removal in an image is obtained by using PCA (principal component analysis) with LPG (Local Pixel Grouping).
Lei Zhang et al., September 2009 proposed that Two-stage image denoising by principal component analysis with local pixel grouping. In this, an efficient image denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG) is presented.
Bochra Bouchhima et al., November 2014 proposed that Dictionary Learning Using EMD and Hilbert Transform for Sparse Modeling of Environmental Sounds. In this, a new dictionary learning method for reconstruction tasks is presented.

4. Proposed Methology

The proposed methodology covers the algorithm used for denoising the noisy image by suppressing noise from a noise-contaminated version of the image. The algorithm is described as follows:
Step 1: Read the original image.
Step 2: Add the noise in the original image with noise level
either 15 or 20 or 25 or so on.
Step 3: Preprocessing is done to get the noisy image after
adding noise to the original image.
Step 4: QM- Analysis is done in this step to represent the
color image as a vector quantity instead of scalar
quantity and covert the image in Matrix form.
Step 5: K- QSVD with Genetic Algorithm is used to denoise
the corrupted image and to get the original image
back.

5. Simulation/ Experimental Results

In this, Genetic Algorithm is applied to the noisy color image generated using K-QSVD to get the denoised color image. Also, mean square error (MSE), peak signal to noise ratio (PSNR) & Structural Similarity Index Matrix (SSIM) are calculated to show the results graphically.

Figure 2 Main window

Above window is main or starting window which has two
Pushbutton one is START and other is EXIT.

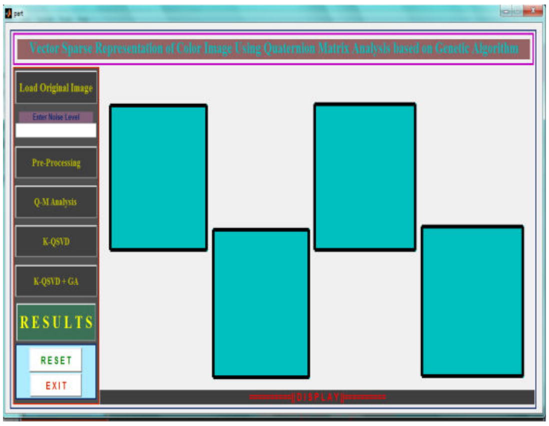

Figure 3 Working window

Above window is working window in this window we push
pushbutton one by one and see the result as shown in the
below window.

Figure 4 Running window

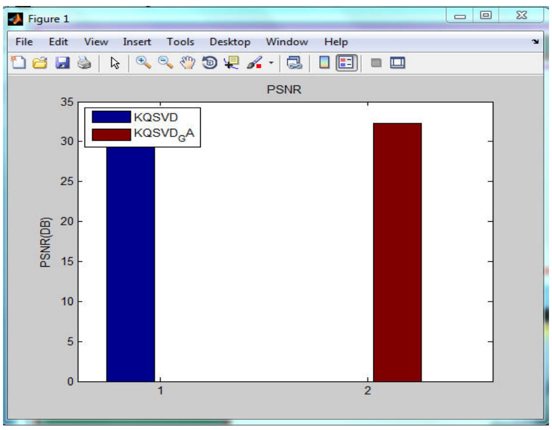

Figure 5 Result of PSNR

This window shows the result of PSNR of previous and
proposed algorithm that shows the quality of image.

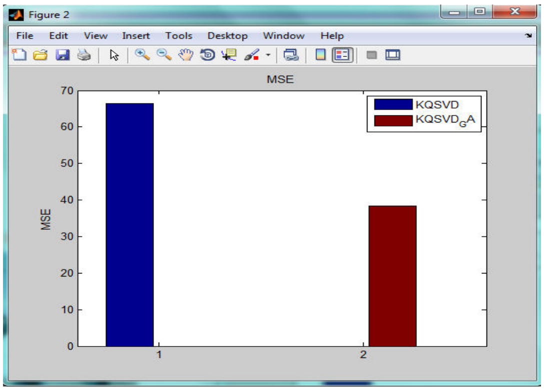

Figure 6 Result of MSE

This window shows the result of MSE (mean square error) of
previous and proposed algorithm

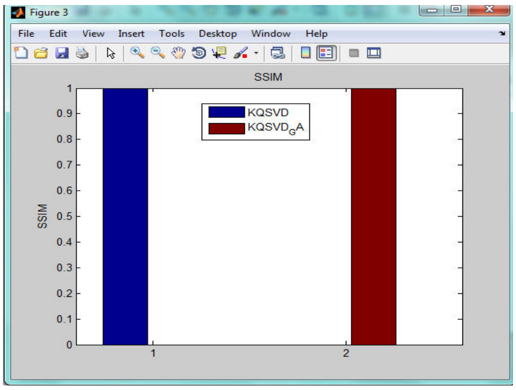

Figure 7 Result of SSIM

This window shows the result of SSIM (Structural Similarity Index Matrix) of previous and proposed algorithm.

6. Conclusion

In this work, we propose "Vector Sparse Representation of Color Image Using Quaternion Matrix Analysis based on Genetic Algorithm". In this work, we only consider the projections of without corrupted pixels onto dictionary in the Quaternion Orthogonal Matching Pursuit. The coefficient vector for every patch p can be approximated only on the non-corrupted pixels using the pruned dictionary by selecting corresponding rows. The computed coefficient vector can be shared with those missing pixels, consulting its validity for the complete patch block. A color image pixel is expressed as a quaternion unit and consequently a color image is formulated as a quaternion matrix. To avoid color distortions we use Genetic Algorithm.

7. Future Scope

In future, Particle Swarm Optimization (PSO) algorithm and Ant Colony Optimization algorithm will be used to avoid color distortions to get better results. Also, currently the usage of the real part of quaternion seems only for three channel color space, the real part is simply set to be zero. This physically meaningful real part will further help us capture color information. In future, we will further explore the potential extension of quaternion sparse model to four color channel space, CMYK in which real part may correspond to the black channel.

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