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Research paper

A Survey: Restoration of Compressed Image

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Abstract

In recent years, blocking artifacts are the one of the major problem faced by the image compression due to quantization bit constraints or inter-block correlation in decompression. The various methods used to remove the blocking artifacts are broadly classified as deblocking methods and estimation / learning based methods. Both the methods are further classified into filtering approach and restoration of transform coefficients, maximum of a posteriori, projection onto convex sets and sparse dictionary learning. All these image restoration techniques are applied to restore the compressed image by considering the compressed image as degraded image. This paper presents various techniques for restoring compressed image and thereby maintaining the perceptual quality of the image.

Keywords: *Blocking Artifacts; Deblocking Method; Maximum of a Posteriori; Projection onto Convex Sets; Sparse Dictionary Learning.*

1. Introduction

The word significance for 'restoration' is to return something to its earlier good condition or position. As the field of image restoration [1] endeavors to obtain the original image from degraded image, where the degradation may be caused due to noise, motion blur or camera misfocus. The purpose of image restoration is to "compensate for" or "undo" the defects which degrade an image. The degraded image is reconstructed by applying inverse procedure or estimated/approximated the corrupted values to restore the original image. This process is also called as image deconvolution or image de-blurring. The image restoration techniques are mainly used to remove the noise which is present in the image.

The aim of image restoration is to identify the attributes of the degraded image itself. Despite of the fact that image restoration process obtains the original image, it is different from image enhancement method since the former method ought to know about the procedure of degradation and the reason for the degradation. But this survey wishes to concentrate on restoration of compressed image by considering the compressed image as degraded image since one of the main problem faced by compression is blocking artifacts [2] in block based transform which is due to course quantization of the coefficients at the edges. In this paper, several methods are discussed which was used in the image processing world to restore compressed image. The Section 2 describes the drawbacks of compressed image and necessity for restoration of compressed image as well as categorizes the various techniques for restoring the compressed image techniques. The Section 3 describes the deblocking methods which discuss various filters used in both spatial and frequency domain and also describes the restoration of transform coefficients. The Section 4 defines the various estimation / learning based approaches which ought to restore the compressed image. The Section 3 and 4 also discusses merits and demerits of each and every technique applied across the compressed image and Section 5 concludes the paper.

2. Restoration of compressed image

The most commonly used image compression standard JPEG (Joint Photographic Experts Group) which achieves high compression ratio but still it suffers from blocking artifacts.ie discontinuities along the block edges or boundaries. The blocking artifacts are mainly due to quantitation bit constraints which usually affects image edges, monotone areas or along the corners of each DCT block. The compression either forms a superfluous edge at inter-block boundaries or blurs the edges that are desired. The visual distortions that the artifacts caused are: false edges are created at inter-block boundaries or changing the texture patterns / blurring the fine edges.

The existing techniques are categorized by George et al.[3] to restore compressed image in spatial domain includes filtering method, estimation theoretic methods and projection onto convex sets methods. Additionally by considering the frequency domain aspects, restoration of the compressed image are categorized as deblocking methods and estimation /l earning based methods. The deblocking methods are further classified as filtering approach and restoration of DCT coefficients. The estimation / learning based methods are further classified as maximum of a posteriori, projection onto convex sets and sparse dictionary learning. Fig. 1 shows the classification of various image restoration techniques.

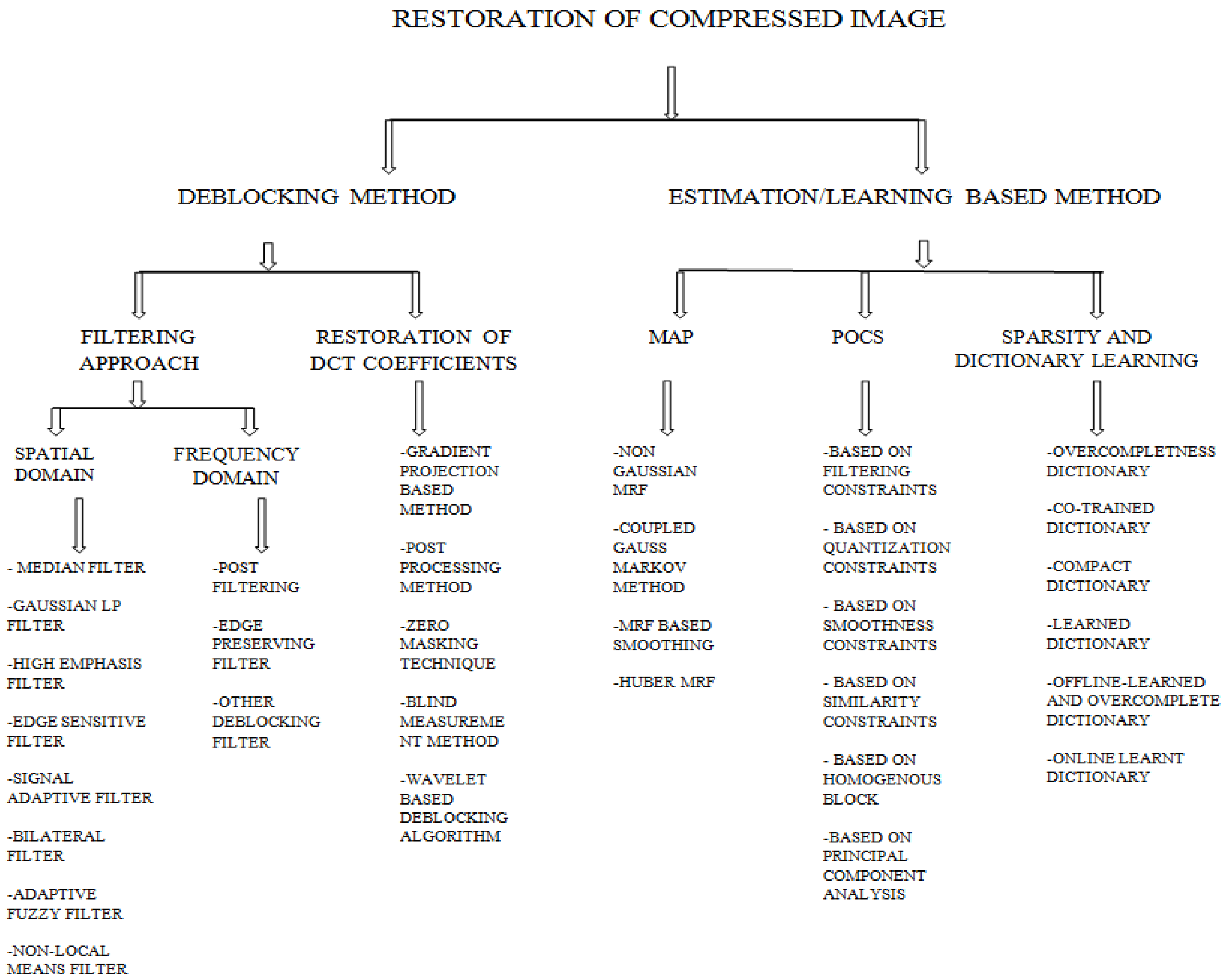

Fig. 1: Classification of Compressed Image Restoration Techniques.

3. Deblocking methods

The block based coding methods such as JPEG produces blocking artifacts that appear as artificial discontinuity between adjacent blocks. The deblocking method is used to recover the original data thereby reducing blocking artifacts. The deblocking method tries to restore the compressed image either using filters or by restoring the DCT coefficients.

3.1. Filtering approach

Filtering is generally used to suppress either the high frequencies in the image, ie, smoothing the image, or the low frequencies ie, detecting edges or fine details in the image (sharpening the image). Restoration of DCT coefficients reconstruct the image transform coefficients directly. The filtering approach is widely classified into two categories.

1) Spatial domain filters.
2) Frequency domain filters.

3.1.1. Spatial domain filters

The spatial domain filters are often used in applications like image enhancement, image denoising and edge detection. In spatial filtering the image plane is directly manipulated based on the neighborhood pixels with the help of the convolution kernels. Here, the spatial domain filters [4]-[13] are classified only based on the removing artifacts in compressed image, where the filters are applied directly on the compressed image.

A separable median filter [4] is used for removing the blocking effects that relies on lower bit-rate image transmission. The normal median filter uses 3x3 window or kernel that is placed on the image. The pixel is replaced by the median of the gray levels from neighborhood of that pixel. But to get rid of blocking effects the traditional median filter is transformed to low-pass filter, once the filter is applied to position of blocking effects. Apart from removing blocking artifacts, it additionally preserves the edges and eliminates noises.

The Gaussian low pass filter [5] uses 3x3 windows or kernel. The coefficients in the window should add to at least one to retain the signal level. The Gaussian low pass filter is employed to remove the blocking artifacts by smoothening the block edges and moreover maintains the sharpness of the image. The filter function is defined as,

$$G(x,y) = 1/2\pi\sigma 2 \quad \left(\frac{e^{-x2+y2}}{2\sigma 2}\right) \tag{1}$$

Where σ represents the standard deviation in Gaussian distribution and x, y represents the horizontal and vertical axis of the original image. The filtering coefficients help to remove the blockiness along the edges. The restored images are still sharp with loss of fine details within the image.

The High Emphasis Filter; HEF [6] proposed by Jarske et.al, uses 5x5 windows or kernel. The coefficients within the kernel are derived from the Gaussian low pass filter, in such a way that when using both filters the step response is zero in the beginning of the step to improves the sharpness. The 5x5 window in this filter helps to enhance the sharpness of the image. However the restored images are still to be improved if there is any noise.

In Edge sensitive Filters [7], the filter coefficients are selected based on the impact of blocking effect within the image. Here, the nonlinear space-variant low pass filter is employed to retain the edge sharpness and smooth the block boundaries. Based on the local characteristics of the images, the pixels wherever blocking effects are extremely visible are filtered by directional lowpass filter and the pixels at edges are not filtered and maintained by the kernel. Therefore, blocking effects is removed without affecting the edge. An edge sensitive filter [8] proposed by Meier et al., is also projected based on a region-based technique for removing blocking artifacts. Here, the degraded image is segmented and each segmented sub image was filtered using a low pass filter. The filter is not applied at the edges or boundaries, so this obstructs the blurring of edges. These filters mainly give more importance to the monotone areas and remove the blockiness in those areas; however the edges in the images are left untouched.

A signal adaptive filter [9] is used to reduce artifacts in compressed image. Before applying filter, the edges are detected by sobel operator and classified based on the edge map, which is obtained through thresholding. A signal adaptive filter which is combined effort of 1D directional smoothing filter and 2D low pass filter of size 5x5 is used to filter the compressed image. It removes the grid noise and therefore the effectiveness is improved by increasing the dimensions of filter coefficients.

The bilateral filter [10] is used for preserving edges that relies on both domain low pass gaussian filter and range low pass gaussian filter. The domain filter highly concentrates on pixels that are close to the center pixel by distributing higher weights to center pixels. The range filter concentrates on pixels that are similar to the gray level of center pixel by assigning higher weights to those pixels. The combined efforts of those filters are extremely applicable in identification of edges. The bilateral filter produces better results in compressed image [11] also to remove blocking artifacts.

The fuzzy filter [12] is a special type of bilateral filter, which applies directional fuzzy filter across sophisticated edges. A smoothing filter is applied across horizontal direction and low pass filter is applied across vertical direction. Both uses sobel operator, which is the first order derivative of the pixels or gradient approximation along horizontal and vertical direction to preserve the edges and remove ringing artifacts. The non-local means filter proposed by Wang et al.,[13] is also used to remove artifacts. The coefficients of the non-local means filter are selected based on the influence of blocking artifacts which are estimated and derived from the difference between quantization noise of the block and the neighborhood blocks. Each block is filtered separately and combined to produces optimal result and thereby reduces blocking artifacts caused due to quantitation constraints.

3.1.2. Frequency domain filters

The frequency domain filters, which deals with transform coefficients[14]-[16], neglects the presence of interference within the image and the restoration is on the footing of the frequency response of correction filter, which was set up for the inverse of the frequency domain. The main reasons for using deblocking in frequency domain are: 1) energy compaction: the transform domain occupies less space since it is often sparsely represented and perform less computation also and 2) direct manipulation: the transform domain coefficients are modified directly before decoding.

The post filtering [14] proposed by Chen et al., is used to filter the block DCT coefficients. The post filtering approach uses the shifted blocks which represents the relationship between the DCT coefficients. First obtain the low-activity of each and every DCT domain blocks. Based on this activity, the filtering techniques are activated. For low-activity block, a large window filter which highly covers the most of the neighborhood is used and for high-activity block, a small window filter is used. Both the different masking filter removes the blocking artifacts. It also identifies abrupt modification in intensity.

In Edge preserving filter, the first step is to identify the relationship between two adjacent blocks in DCT domain based on its boundary pixels [15]. The discontinuities along the boundary pixels are recovered by using the relationship derived from the two adjacent blocks. Normally for the non-smooth areas like edges and strong textures, the frequency properties of two blocks differ from each other. Based on frequency properties, the DCT filtering is applied across smooth areas and edge preserving smoothing filter called sigma filter [2] is applied across non-smooth areas. It not solely removes blocking artifacts, but also smoothens some unwanted blocks.

Another Edge preserving filter [16] is used to filter the DCT coefficients relies on the edge map. Based on the analysis of edge map, smoothing and edge preserving filter are used. It reduces the ringing artifacts and thereby preserving the details or edges by combining the filter results.

The Other deblocking filters [17] - [22] are adaptive in nature ie. Based on the observation of the image, the different filters or modes are selected. The deblocking filter proposed by Kim et al., [17] has totally two different filtering modes where the filter performs either one-dimensional filtering or modifying the adjacent pixels. The filtering process consists of two steps: mode decision, filtering the smooth region mode, and filtering the default mode. The first step is to identify the mode based on recognizing the flatness of in each row or column respectively. A nine-tab low pass filter is applied across the smooth regions and for the other regions only the pixels are modified based on the adjacent vertical block boundary. It adapts the various image features successfully and highly adapted by real time applications but still it produces noticeable artifacts in flat regions. The deblocking filter is also designed for H.264 and MPEG 4 video sequences. [18].

A deblocking filter proposed by Tai et al., [19] is used to restore the compressed image based on 1-Dimensional filtering of block boundaries, on compressed image. To achieve effective deblocking three different modes are used. The strong filters are used across block boundaries. An intermediate filters are used to balance strong filtering in smooth regions and weak texture and true edges. This method preserves the high frequency components while smoothen the blocking artifacts at very low computational cost. The smooth and non-smooth areas are not identified easily. High frequency components are preserved highly, while smoothing blocking artifacts with low computational cost. The textures of low-frequency components are eliminated. And also it is difficult to identify smooth and non-smooth areas.

The deblocking filtering using sum of symmetrically aligned pixels [20] is proposed for reduction of blocking artifacts in images and video. The basic weights are obtained from a aligned weighted sum of pixel quartets which obeys predefined constraints. A deblocked image is produced using these weights which contain blurred edges near real edges. To prevent the blurred image, modify the non-monotone area weights of pixels by predefined factor called a grade and the method is called as Weight Adaptation By Grading (WABG). Repeat the process of calculating WABG for three iterations. In the fourth iteration, the remaining portions of the image are deblocked to form detailed blocks and this process is called as Deblocking Frames Of Variable Size (DFOVS). The WABG and the DFOVS calculation produce better results across areas except the monotone areas on the decompressed image.

An adaptive deblocking method [21] uses a transform table with different dimensions of DCT. This algorithm applies a deblocking procedure identify adjacent three blocks and applies three different low pass filters across the DCT values of the blocks which preserves the fine details of the image. The transform table is used to store the different dimension DCTs for reducing the computational cost. This method shows improvement in the subjective image quality with distinguished effects. The adaptive deblocking achieves subjective quality improvements with less computational efficiency but still it suffers from ringing artifacts.

A deblocking filter [22] is also used to restore the compressed image. To remove the smoothing and non-smoothing areas in a compressed image, a few DCT coefficients are modified and then apply smoothing filter which highly concentrate on the intermediate region without affecting edges. The filters are designed to reduce discontinuities based on the correlation between neighbouring blocks. The filtering approaches mainly concentrate on the specific areas especially edges of the images which may lead to over smoothing of that areas and their by affecting the perceptual quality of the image or causes ringing artifacts. This ringing artifact can be identified easily by estimation methods.

3.2. Restoration of transform coefficients

The Restoration of Transform Coefficients [23]-[27] reconstructs the image transform coefficients directly. The image transforms coefficients after quantization of compressed image is taken into consideration which has one DC coefficient and 63 AC coefficients. The gradient projection based method [23] is primarily based on the theoretical approach by observing the quantized DCT coefficients in two neighboring blocks. This method is mainly based on increasing the Mean Square Difference of Slope; MSDS between the slope across two adjacent blocks and the average between the slopes of each of the two blocks closes to their boundaries. So, that the inverse quantization reduces the MSDS. To increase MSDS, the widths of quantization intervals of transform coefficients are altered. Consequently, for the inverse quantization, the MSDS is reduced by an appropriate quantity that is likely to reduce the blocking artifacts. This method reduces blocking artifacts solely based on subjective approach.

The Post processing method [24] modifies the quantized transform coefficients of the decoded image. This technique generates a compensating signal from the quantization error patterns, since it is evident that the quantization error affects successively within the vertical and horizontal directions over all of the N x N spatial locations. The compensating signal is then added with the received blockly image along the edges, in order to have minimum block discontinuities along the boundaries.

The zero masking technique [25] provides the solution for blocking artifacts in compressed image. To strip down the blocking artifacts, first compare the two adjacent blocks of compressed image in both horizontal and vertical directions and determine the visible boundaries between blocks. Then represent a new block with this visible boundaries and 2D step function with noise. And then perform DCT on such block to identify some AC coefficients which are fixed throughout and strip down such AC coefficients to zero to remove blocking artifacts to some extent ie, the zero masking techniques obtains sensible results at terribly low bit-rates.

The blind measurement method [26] initially design a model for each block of compressed image as 2D step function and then measure the properties of blocks like texture, luminance or brightness. The edges in the block are determined by considering a threshold value and this value is compared with measured value of two adjacent blocks. If the measured value is less than threshold value then no processing is needed. If the measured value is greater than or adequate to threshold then anyone of the adjacent block is taken into account as edge block. Eliminate these extra edge block using filtering since it’s the artifacts created due to compression.

The wavelet-based deblocking algorithm [27], first determine the approximate threshold value that is obtained by finding average difference between horizontal and vertical directions. However a number of the block discontinuities in the image may be due to genuine edges, during this case if the threshold value is calculated it creates large discontinuities; over estimation of the threshold value. If the threshold value is calculated for smooth areas it produces no discontinuities along the block boundaries; under estimation of threshold value. Based on the threshold value the quantization constraint and the range constraint are added with the deblocked image. The algorithm suppresses blocking artifacts and ringing artifacts effectively by protecting true edges.

4. Estimation/ learning based methods

In Estimation / learning based methods are further classified into Maximum of a-Posteriori; MAP [28]-[32] in which a block or pixel is restored based on the estimating an unknown quantity that equals to the mode of posterior distribution, Projection Onto Convex Sets; POCS [33]-[40] which restore a pixel based on the convex set derived from the original image and Sparse dictionary learning [43]-[48] is a representation learning method which aims at finding a sparse representation of the input data, in the form of a linear combination of a small number of basis function or basis function itself. These elements are called atoms and these atoms compose a dictionary.

4.1. Maximum a-posteriori probability

The Quantization process during compression creates the blocking artifacts. In order to restore the compressed image, first estimate or find the lost quantization coefficients. One amongst the estimation methods is maximum of a posteriori [28] that is used to estimate the unknown quantity based on Bayesian statistics. The MAP is a stochastic process which estimates the unknown quantity that equals to the mode of posterior distribution whereas the posterior suggests that taking into account the relevant evidence related to a particular code being examined.

Markov Random Field; MRF defines the random variables which satisfies Markov property for describing the image model. The Markov property is a stochastic process based on conditional probability defines the future states of the process which depends on the present state but not based on the past. A new method proposed [29] is based on Non-Gaussian Markov random field in which quantization step divides the transform coefficients and maps all these coefficients in a partition cell to a particular point of reconstruction by taking the centroid of cell. During decompression, MAP is estimated by using gradient projection method which iteratively selects the reconstruction point that fits a non-Gaussian Markov random field image model effectively. The Gibbs measure is used to represent the distribution of MRF’s. From experimental results, reconstructed image sequence shows a reduction in artifacts.

The Coupled Gauss-Markov method [30] consists of two layers, one representing the discontinuities of the arbitrary field and other representing the intensity values that are determined. This method uses the priori information which describes the intensity of the original image by using non-stationary Gauss – Markov model. During the decompression the decoder is used to estimate MAP estimate by using mean field annealing which is iteratively carried out to find maximization of posterior function. The prior information also called prior constraints is also integrated into the estimator to boost the quality of reconstructed image.

Markov Random Field based smoothing [31] partitions the degraded image into segments based on monotone areas and texture. Each textual and monotone region is smoothened separately to forestall edge blurring and solely the dominant edges are estimated using MRF.

The Huber MRF method [32] is employed to acquire the original DCT coefficients by using the maximum a posteriori estimation. In order to obtain the optimized result of original DCT coefficients are estimated using an image prior model and a quantization noise model. The image prior model is based on block similarity approach which calculates local similarity of the blocks coefficients in each sub band and adds sample weight to measure block similarity which eliminates negative assumption. The quantization noise model applies the quantization coefficients as an estimator. The original value is estimated based on the two models which recuperate the original value.

4.2. Projection onto convex sets

One of the main applications of projection onto convex set [33] is to discover missing pixels in image and video and thereby reducing blocking artifacts in it. In this theory, the information of original image which are priory known are represented as convex set. After deriving the convex sets, define the projection operators used. Obtain the set that are closest to the point by projecting a point onto a convex set. The convex set is also called as constraint set. Numerous constraint set are homogeneity constraint set, quantization constraint set, smoothness constraint set etc. The primary step in projection onto convex set is to identify the missing pixels or recovery vectors and therefore the second step is to create two or more convex constraints using surrounding vectors. It is an iterative procedure to identify the missing pixels.

The theory of projection onto convex sets is an iterative block reduction technique [34]. A minimum of two constraints on coded image are used for restoration into original form. During this one of the constraint can be devised from the blocking artifact image, which has high frequency components across boundary of neighboring blocks in both vertical and horizontal directions and named as called band-limitation constraint or filtering constraint. The second constraint is derived from quantizer which is named as quantization constraints. The projection of artifact image onto original image is performed by iterative procedure. These iterations are repeated till artifact free image is obtained.

POCS based on quantization constraints [35] is a recovery algorithm that adaptively filters the DCT domain. The three steps in recovery algorithm: First step identifies the local properties of pixel's intensity. Second step introduces three constraint sets based on smoothness, filtering and quantization constraints. Third step uses projections to identify the pixel intensity. The algorithm converges after 3 to 5 iterations and requires both forward and inverse DCT in each iteration, which creates high computational complexity.

POCS based on smoothness constraints [36] relies on line processes modeling where new families of directional smoothness constraint sets are represented. Because of the fact that visibility of artifacts in an image is spatially varying, the definition of smoothness sets are also considered. The numerical computations for the projections onto these sets are minimized by a Divide-And-Conquer; DAC strategy to preserve edges. The algorithm can remove blocking artifacts from compressed image and video.

POCS based on smoothness constraints [37] and quantization constraints which is derived from DCT correlation is especially applicable in Digital High Definition Television; HDTV images that reduces blocking artifacts.

POCS based on similarity constraints [38] is employed to reduce blocking artifacts that is predicated on POCS by considering highly correlated images. As assumed images are highly correlated, the frequency characteristics between two adjacent blocks are similar to the frequency characteristics in each block. Only the high frequency components with global characteristics of decoded image which causes blocking artifacts are considered. The local and global characteristics are obtained by applying N-point DCT and 2N-point DCT respectively. The high frequency components which cause blocking artifacts are retrieved by comparing the local and global characteristics. From the results, the convex sets and also the projection operators are outlined that improves the performance compared to conventional techniques.

POCS based on homogeneous block [39] is employed to identify high frequency components that cause blocking artifacts. The homogenized blocks are those blocks in which no adjacent pixel difference is larger than the difference of the block boundary. Identify two adjacent homogeneous blocks and examine the local characteristics of the homogenous block. Then compare the two homogenous blocks and derive the relationship between the coefficients that detects the high frequency components. This method is useful in evaluating the both still and moving images. The key advantage is that it preserves the original edges.

Projection onto convex sets based on principal component analysis is used to identify the missing intensities in the target compressed image. The kernel principal component analysis is principally used for extracting non-linear features like texture [40]. In the reconstruction steps, first obtain the nonlinear eigen spaces from the local images having the identical texture and embrace them into constraint set of POCS. Based on the converged error of the target image, the optimal non-linear eigen spaces are designated for reconstruction process. This method is extremely effective in image restoration, image enlargement and missing area identification.

4.3. Sparsity and Dictionary Approach

The goal of sparse representation is to approximate a natural signal by a linear combination of a small number of elementary components; called atoms ie. number of atoms is greater than the dimension of the signal. From the view point of the atom [41] the sparse representation is classified into two: naïve sample based and dictionary learning based. The two methods for designing dictionaries are: The first one is the analytical method [41] [42], which derive the dictionary from a set of mathematical assumptions or matrix factorization which produces set of signals. This approach approximates the signals of interest as coming from simpler classes of mathematical functions, and designs efficient analytic dictionaries for those simplified classes. The second one is the learning methods, which infers the dictionary from signal realizations via machine-learning techniques such as principal component analysis [42], kmeans etc. This approach replaces prior assumptions on the signal behavior with a training process which constructs the dictionary based on the observed signal properties. Thus the learned dictionary is adaptive to the observed signals. The various dictionary learning approaches are given below.

Sparsity and over completeness dictionary [43] means the number of basic elements in the dictionary is greater than the vector space spanned by the input vector. Given a pair of images, this method learns a dictionary for each image and computes how sparsely one image is approximated using the dictionary extracted from the other either separately or together which includes regularized compression, in reverse problems and feature extraction. The sparsity of the wavelet coefficients of natural images are attributed to the success of JPEG2000 standard. Sparsity and over completeness extends the advantages in compression of images, separation of texture and cartoon content in images and inpainting. But to extract the sparsest representation is a hard compared to designing the proper dictionary for reconstruction of sparsity model. An over complete dictionary are designed with two steps. The first step finds the coefficients from the predefined transform such as wavelets, discrete cosine transform, curvelets, fourier transform or the combinations are used. Then the second step updates assuming fixed and known coefficients from the training-set which is highly suitable to describe the signal sparsely.

The Co-trained dictionary [44] is used in image matting. Co-trained dictionary learning methods uses training-set which derives the relationship between image patches with high resolution and image patches with low resolution called as alpha matte pair. The two dictionaries D_l,D_h defines the alpha-matte pair, which are extracted from low-quality compressed image and high quality compressed image / uncompressed image. This approach synthesizes the image details based on alpha matte pair derived from the training-set. A variety of object structures can be incorporated by expanding the number of dictionaries.

A sparsity-based soft decoding [45] approach is to directly used to restore transform coefficients and thereby prevents the influence of quantization errors in the image domain. For each DCT block a compact dictionary is learned by grouping the sample blocks which are collected via non-local patch based on principal component analysis. Using collaborative sparse coding approach the corresponding DCT coefficients are estimated which results in block specific dictionary which also considers the similarity between sample DCT patches during dictionary construction. Inter-block correlations are totally ignored but still produce some ghosting artifacts along edges.

The learned dictionaries are used in image analysis initially. JPEG decompression using a learned dictionary [46] approach is introduced for reducing the artifacts that are created while JPEG decompression. The JPEG images are decompressed by following steps: lossless decoding, de-quantization and computing the inverse DCT to each block. The data adaptive learned dictionary process is done by two steps. The first step creates the dictionary

D via K-SVD de-noising method which identifies the sparse coefficients and denoising patches. The second step performs total variation regularization across the denoising patches.
Offline-learned over complete dictionary [47] method which reconstruct a group of neighborhood pixel patch using two priors. These priors are used to overcome quantization bit constraints. In first step, each pixel patches are approximated as sparse signal representation prior from an over complete dictionary which was trained from a set of natural images. In second step, a graph signal prior derived which represents the structure of target image. From the two image priors, the high frequency textual areas are used for reconstructing the signal.
Online learnt Dictionary [48] is a Dual domain approach. The previous paper [47] stated that DCT domain is restored. To incorporate high frequency priors of uncompressed image, the sparsity based approach is used to restore pixel value after DCT domain. The two online learnt dictionaries in transform and pixel domain is observed for restoration. It exploits residual redundancies. It recovers high frequency information driven from a large training set. Since both the dictionaries have individually learned for each patch, it allows extra flexibility with heavy computational cost. In learned dictionary, the details about the image restoration will be present based on which images will be restored into its original form by eliminating the noises present in that image.
The dictionary learning approach is also highly applicable in medical image reconstruction of photo acoustic Computed Tomography [49] and MRI; Magnetic Resonance Imaging [50]. In photo acoustic computed tomography, the sparse dictionary (designed by combination of wavelet transform and discrete cosine transform) is used to capture important features of the photo acoustic signal and the total variation optimization method is used to reconstruct the image. In MRI, the proposed method is an iterative approach which applies trained transforms, thresholdings dictionaries to images and finally least squares update of the image. It reconstructs the image by minimizing a minimum absolute error criterion. In both these methods dictionary learning procedure produces effective results.
After designing the dictionaries, various optimization methods are used to find the solution for the given sparse element from the dictionary. The various optimization methods / algorithms are FOCUSS; Focal Underdetermined System Solver [51], MOD; Method of the optimal direction, KSVD; K-Singular Value decomposition [52], Orthogonal Matching Pursuits [53]. Apart from image restoration the sparsity based dictionary learning [54] also supports various other applications like image inpainting, image denoising, image classification etc.

5. Conclusion

Even though lots of transforms are evolved after Discrete Cosine Transform such as Discrete Wavelet Tansform, Curvelet, Contourlet, ridgelet, shearlet etc, the JPEG compression which uses Discrete Cosine Transform plays a vital role in image compression. The techniques discussed in this paper concentrates mainly on perceptual quality of the DCT based compressed image since DCT supports strong energy compaction. The restoration methods discussed in this paper has its own pros and cons. From the comparative study it is clearly evident that, the deblocking filtering approach mainly deals with compressed image in both spatial and frequency domain. The deblocking method for restoring the DCT coefficients is based on theoretical approach which tries to calculate the quantized transform coefficients. The estimation methods based on MAP mainly focused on estimating the unknown quantity or lost quantitation coefficients using various models. The POCS estimation creates convex set where the elements are derived from various constraints and the unknown quantity is derived by projecting a point on these convex set. But the dictionary learning approach creates dictionary based on more than one transform domain to obtain the unknown quantity. The dictionary learning approach is widely used in all fields of image processing like compression, denoising, enhancement and here it removes both blocking and ringing artifacts in the image and achieves best state-of -art image at high computational cost. The quality of the reconstructed image is measured by SSIM; Structural Similarity Index and MSSIM; Mean Structural Similarity index by comparing the compressed image with reconstructed image.

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