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LOW RANK DECOMPOSITION BASED RESTORATION OF COMPRESSED IMAGES VIA ADAPTIVE NOISE ESTIMATION

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Abstract – Images coded at low bit rates in real-world applications usually suffer from significant compression noise, which significantly degrades the visual quality. Traditional denoising methods are not suitable for the content-dependent compression noise, which usually assume that noise is independent and with identical distribution. In this paper, we propose a unified framework of content-adaptive estimation and reduction for compression noise via low-rank decomposition of similar image patches. We first formulate the framework of compression noise reduction based upon low-rank decomposition. Compression noises are removed by soft thresholding the singular values in singular value decomposition of every group of similar image patches. For each group of similar patches, the thresholds are adaptively determined according to compression noise levels and singular values. We analyze the relationship of image statistical characteristics in spatial and transform domains, and estimate compression noise level for every group of similar patches from statistics in both domains jointly with quantization steps. Finally, quantization constraint is applied to estimated images to avoid over-smoothing. As an enhancement; this project is implemented with Local ternary Patterns (LTP) for further improvement in image clarity. LTP utilizes a global histogram quantity for image characterizations to improve reliability and security.

Index terms – Block transform coding, compression noise, denoising, low-rank, SVD.

INTRODUCTION: Along with the fast development of portable digital devices, e.g., digital cameras and smart phones, more and more images and videos are captured and shared through Internet or mobile networks. Due to the limitation of bandwidth, the shared images and videos are usually compressed at low bit rates, and their qualities are severely degenerated by compression noise. These low quality images are not only with poor user experience but also deteriorate the performance of many computer vision algorithms, which are mainly designed for uncompressed images and videos. In order to improve the quality of compressed images, there are lots of image denoising methods proposed in recent years. Most of the existing denoising algorithms assume additive white Gaussian noises, which are independent and with identical distribution in a whole image. In general denoising procedures, the standard deviation of noise is usually assumed known and utilized to control filtering strength to avoid smoothing image structures excessively. In this paper, we investigate the compression noise estimation and reduction for block-discrete cosine transform (BDCT) based compression. Since compression noises are mainly generated by quantizing transform coefficients, they are dependent on the distribution of coefficients. To remove compression noise as much as possible, we propose a content-aware method to reduce compression noise by dividing images into different groups of similar image patches. For each group of similar image patches, we formulate the compression noise reduction as a low-rank optimization problem, and solve it via soft-thresholding the singular values in singular value decomposition (SVD) of group of similar image patches. Since the thresholds for singular values are directly related with compression noise levels, we also propose a content-dependent compression noise estimation algorithm. First, we derive the distribution parameters of coefficients from image correlation model. Then, we derive the standard deviation of compression noise for each group according to coefficient distribution and quantization steps. Finally, we take the weighted average of all these estimated patches to restore original images. To avoid over-smoothing, narrow quantization constraint (NQC) [1] is applied to the restored image. Therefore, our method with content-dependent noise estimation is different from previous works, which only utilize a global noise level by assuming i.i.d for compression noise. Extensive experimental results show that our method can significantly improve the quality of compressed images, and it is also helpful for computer vision tasks as a pre-processing method.

LITERATURE SURVEY

a) Block Transform Image Coding

Block transform coding is the most widely used image coding framework, in which the block discrete cosine transform (BDCT) is adopted by most of popular image/video coding standards, e.g., JPEG [2]. In a typical BDCT coding framework, an input image, I, is divided into non-overlapped N × N blocks. Each block is transformed into frequency domain using DCT, and then the transform coefficients are quantized independently, and compressed by entropy coding. At the decoder side, the inverse procedure is carried out to reconstruct images. The whole process can be described as,

$$\mathbf{X}_{\mathcal{B}} = \mathcal{T}(x_{\mathcal{B}}), \quad (1)$$

$$\mathbf{Y}_{\mathcal{B}}(u,v) = round\left(\frac{\mathbf{X}_{\mathcal{B}}(u,v)}{Q(u,v)}\right)Q(u,v), \quad (2)$$

During the above process, the main source producing compression noise is quantization in Eqn.(2). Since coefficients in high frequency bands are very small for most image blocks, the quantization operator may directly make them zeros, which leads to insufficient coefficients to represent image local structures and may generate ringing artifacts around edges. In addition, due to the loss of inter-block correlation in quantization process, similar coefficients in neighboring blocks may be quantized into different ranges, which leads to discontinuities at block boundaries, referred as to be blocking artifacts.

b) Compression Noise Reduction Methods

The methods can be roughly classified into two categories, general denoising methods and specific denoising methods. General denoising methods usually assume noise following independent identical distribution, and utilize some image prior models. Besides the image prior models, specific denoising methods further take advantage of some side information on noise to improve their performance, e.g., quantization steps in compression noise reduction. This paper will focus on compression noise reduction problem. Although general denoising methods also can alleviate the compression artifacts, e.g., BM3D [3] and CSR [4], their performances are not as good as that in removing noise with independent identical distribution (i.i.d). Therefore, a lot of denoising methods specially designed for compression noise are proposed in literatures. Reeve and Lim [5] smooth out the blocking artifacts by directly applied a 3 × 3 Gaussian filter to the boundary pixels. In [6], a nonlinear space-variant filters based on edge-oriented classifiers is utilized to reduce blocking artifacts while preserving image edges. To avoid oversmoothing image textures, Minami and Zakhor [7] utilized the quantization intervals of transform coefficients as a convex set to constrain the filtered coefficients. In the latest video coding standards, e.g., HEVC [8], the strength of deblocking filter is adaptive according to coding modes, and the adaptive loop filter (ALF) [9], [10] in HEVC is utilized to reduce the coding artifacts by deriving Wiener filters in encoder side. Maggioni et al. extended BM3D by utilizing temporal information to reduce video compression noise and estimated a global noise level for each frame based on quantization steps.

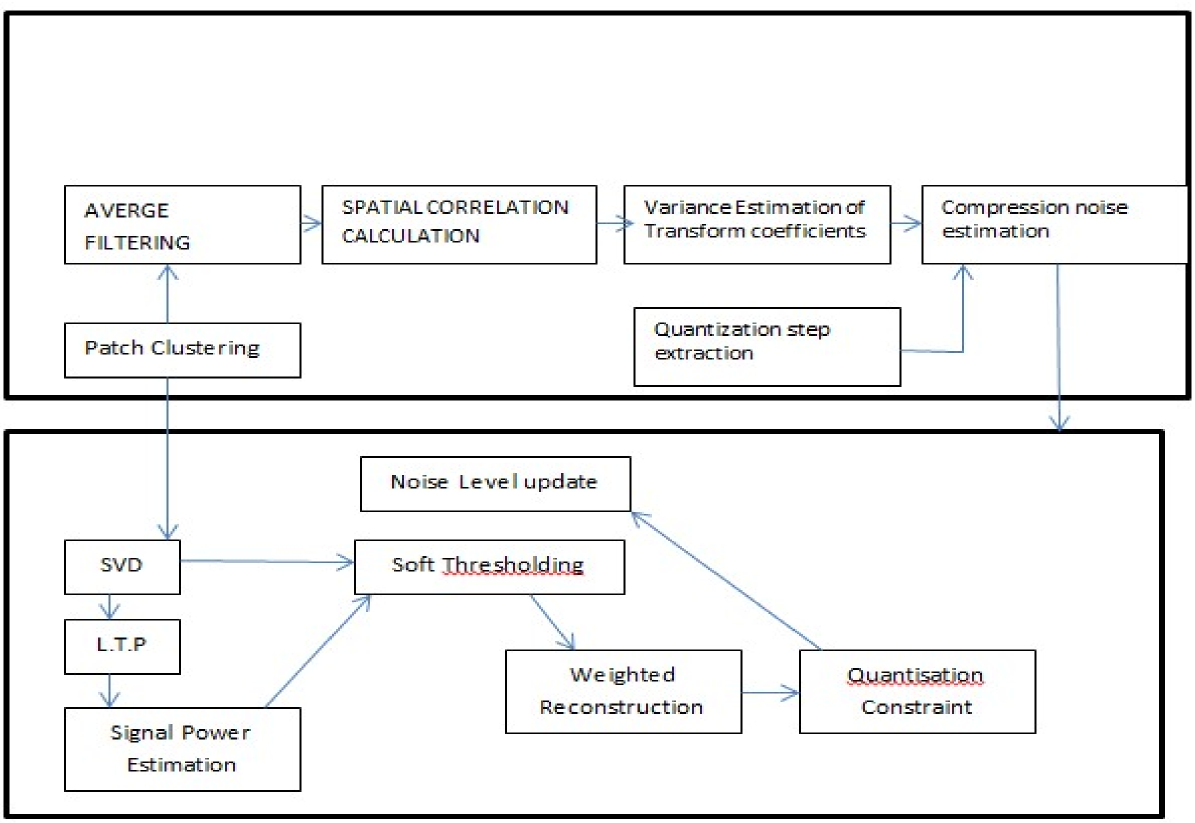
c) Noise Level Estimation

Noise level, e.g., standard deviation of noise, is generally utilized to adjust the filtering strength of denoising. However, in practice, the noise level is unknown and need to be estimated from noisy images,which is also a difficult problem, especially for content correlated noise. An intuitive method to estimate noise level is to calculate the standard deviation of difference between noisy image and filtered image by low pass filter Obviously, this method is difficult to get accurate noise level estimation, because low pass filter is inefficient to remove content-dependent noises.

Considering image sparsity in transform domain, Donoho proposed to estimate noise variance from the coefficients in diagonal bands of image wavelet decomposition. Liu et al. estimated content uncorrelated noise level from single image by applying PCA to weak texture patches. Ponomarenko et al. utilized the K most similar blocks in an image to estimate noise variance by applying median filtering operation to these blocks in DCT domain.

Colom et al. further extended the method to estimate the variance of noise according to the intensity and the frequency. Ponderated MSE is proposed to measure the similarity among image patches to reduce the negative effects of noise, by giving higher importance to the low frequencies of the blocks. Colom et al. further proposed a multiscale approach to improve the estimation accuracy for noise low frequencies, which may not be captured by a small image patch in original resolution. This method efficiently improves the performance of the intensity-frequency dependent noise reduction. However, the compression noise is more complex, and is difficult to describe by a simple model, e.g., polynomial, based on image intensity and frequency.

PROPOSED WORK



In the proposed compression noise reduction method, a compressed image, *Iy*, is divided into a set of overlapped *p* **p* image patches firstly, denoted as *target patches*, which are extracted every *s* pixels (denoted as *overlapped step*) along raster scanning order, and they are overlapped when $s < p$. For each *target patch*, the K most-similar patches (including itself) are found in a $R \times R$ neighborhood around it ($R = 31$ in this paper), and these similar patches are denoted as *reference patches* and selected according to their similarity measured. We call this procedure *Patch clustering* as shown in above Fig. Since compression noise levels for image patches with similar structure are usually approximate, a potential advantage of similar patch clustering is that it is convenient to adjust the control parameters of denoising algorithms according to image content group by group. Considering the overlapping of image patches, there may be multiple estimations for one pixel generated from different groups. In order to reconstruct image while avoiding oversmoothing, after all the image patch groups are processed with soft-thresholding, we reconstruct image by taking the weighted average of overlapped image pixels from different image patches. Since compression noise is directly generated by quantizing transform coefficients, its distribution is not only related with quantization steps but also correlated with distribution of transform coefficients.

a) *Singular Value Decomposition*

SVD strategies manage taking care of troublesome direct slightest squares issues, for example, the terms in archives case and here hues in pictures. They depend on the accompanying hypothesis of Linear Algebra4: "Any M x N grid A whose quantities of lines M is more noteworthy than or equivalent to its number of sections N can be composed as the result of a M x N segment orthogonal network U , a N x N askew framework W of particular esteems and the transpose of a N x N orthogonal lattice V**:**

$$\begin{pmatrix} A \end{pmatrix} = \begin{pmatrix} U \end{pmatrix} \begin{pmatrix} \mathbf{w_1} & & \\ & w_2 & \\ & & \mathbf{w_N} \end{pmatrix} \begin{pmatrix} V \end{pmatrix}$$

Subjectively the U network speaks to a vector reason for the most pertinent data in the framework while the eigenvalues wi speaks to the changeability in the data.

SVD Solution Applied To Similarity Search By Colors:

The Singular Value Decomposition (SVD) Solution to the issue of hunting a huge database down comparative pictures by hues can be connected in the accompanying way : we can imagine building an A framework (utilizing the documentation above) relating to the 16M shading histogram of a heap of pictures whereupon we might want to do picture shading likeness examination. All together that the SVD procedure can be a helpful and useful observational kind of model, we have to exhibit that we can construct an A grid that is sparse 4,6 and that the disintegration can be performed by reasonable numerical streamlined technique.

SVD Solution: Implementation And Experiments:

We utilized the SVD bundle (SVDPACKC 6) from the NetLib store. Specifically we utilized an iterative technique, for example, the Lanczos strategy for deciding a few of the biggest particular triplets (solitary esteems and comparing left-and right-solitary vectors) for extensive meager networks. For our tests, we utilized a heap of 1999 jpeg pictures (133 x 100 pixels). We adjusted the las2 (Lanczos strategy) program of the bundle to change the information prerequisites for our conditions (substantially bigger inadequate network).

We built 16M (RGB shading model) shading histograms to manufacture the A grid : sections distinguish picture through a reasonable ID while columns portray a shading record C (mix of R,G,B esteems giving one of 16M hues esteems). Testing demonstrated that with a specific end goal to build a scanty lattice and having the capacity to run the SVD bundle, we needed to diminish the viable number of hues in the histogram from 16M to 65,536. We ran the SVD bundle on a Digital Alpha Linux machine (two Alpha 21264 667 MHZ CPUs with 4 MB reserve, 1Gb SDRAM).

Developing the SVD scanty framework created the accompanying conditions:

- 234 Mb of transitory stockpiling to deal with 1999 shading histograms of 65536 shading canisters
- Final meager network organized utilizing just non-zero esteems utilized 78 Mb.

Asking for 200 eigenvalues delivered a run time of around 20 minutes. Figure demonstrates an ordinary outcome to be specific the N biggest particular esteem (eigenvalues) that holds the most important data contained in the shading histogram of a pile of pictures.

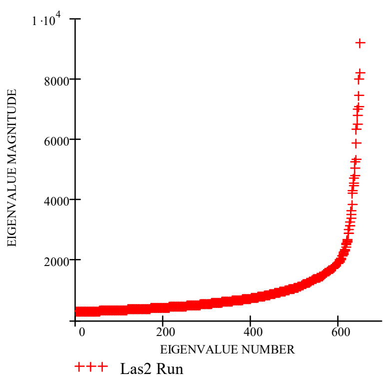


Fig. 1: Results of a SVD run.

The values that show the most variability are the retained relevant Eigen values for this problem**.**

b) *Dimension Reduction Results***:**

The particular esteem deterioration of the (65536 x 1999) lattice A yields another 65536 x N network T containing the left solitary vectors or U grid (the left solitary phrasing is clarified in the SVD bundle) comparing to the N biggest solitary estimations of An as represented in Fig. 1 (Fig. 1 demonstrates the case for 700 asked for eigenvalues). The N biggest esteems held as much data about the first histograms of the pile of pictures. The framework T is utilized to extend 65,536 dimensional hues histogram into a N-dimensional space shading histograms utilizing:

$$H_{65536} \, T = H_N$$

We can look at the comparability of pictures base on straightforward 512 shading canisters Histograms versus the SVD lessened N-histograms to survey the handiness of SVD dimensionality decrease. It is discovered that for about N = 50 eigenvalues (the most biggest esteems) we get a similar likeness measure of picture examination utilizing the outstanding P(10) metric utilized as a part of content web search tool advancement. Subsequently SVD Process seems, by all accounts, to be a productive exact technique to diminish the measure of any capacity depicting picture properties for closeness reason.

SVD is a dimensionality diminishment method, which is utilized on the lattices to deliver a low rank estimation of it. On the off chance that there was M x N network A with rank r, the utilization of SVD on it will be [14].

$$SVD(A) = U \times S \times V^T \qquad (3)$$

Where, S is a corner to corner grid called the Singular lattice, their slanting sections have the property Si > 0, and Si > Si+1, and those passages speak to the Eigen estimations of the framework A. The various passages have the estimation of zero. U and V grids are orthogonal lattices, and their first r sections speak to the orthogonal Eigen vectors comparing to Eigen esteems in the S framework. SVD is a reversible procedure, thus by having the three grids U, S and V we can determine the first framework A from them by utilizing condition. By utilizing SVD, the incentive altogether is 48 for each picture due to resize the pixel/grid of the pictures from 4000x3000 into 64x48. These qualities demonstrate for one individual of one picture as it were. There are 10 pictures for each subject, in this way altogether for 18 people is equivalent to 180 pictures (10 pictures for every subject). Along these lines, each subject will have 480 SVD esteems. From SVD esteem, the exploration is watched and found that the esteem gives marginally same starting with one individual then onto the next individual. The following is the charge to discover the SVD esteem for each picture.

```
A=im2double(C);
A2=svd(A);
RES1(k,:) = A2;
```

The main line is to changes over the power picture C to twofold exactness, rescaling the information if important. On the off chance that the information picture is of class twofold, the yield picture is indistinguishable. The second line is to figure the SVD esteem.

Solitary esteem decay takes a rectangular network of quality articulation information (characterized as A, where A will be a n x p grid) in which the n lines speaks to the qualities, and the p sections speaks to the exploratory conditions. The SVD hypothesis states:

$$\mathbf{A}_{nxp} = \mathbf{U}_{nxn}\, \mathbf{S}_{nxp}\, \mathbf{V}^T_{pxp}$$

Where

$$\mathbf{U}^T\mathbf{U} = \mathbf{I}_{nxn}$$

$$\mathbf{V}^T\mathbf{V} = \mathbf{I}_{pxp}$$ (i.e. U and V are orthogonal)

Where the segments of U are the left solitary vectors (quality coefficient vectors); S (an indistinguishable measurements from A) has particular esteems and is corner to corner (mode amplitudes); and VT has lines that are the correct particular vectors (articulation level vectors). The SVD speaks to a development of the first information in an arrange framework where the covariance lattice is inclining. Ascertaining the SVD comprises of finding the eigenvalues and eigenvector of AA^T and A^TA. The eigenvectors of A^TA make up the sections of V, the eigenvectors of AA^T make up the segments of U. Likewise, the solitary esteems in S are square underlying foundations of eigenvalues from AA^T or A^TA. The solitary esteems are the corner to corner passages of the S lattice and are masterminded in sliding request. The particular esteems are constantly genuine numbers. In the event that the grid A will be a genuine framework, at that point U and V are likewise genuine.

To see how to illuminate for SVD, how about we take the case of the lattice that was given in Kuruvilla et al:

$$A = \begin{bmatrix} 2 & 4 \\ 1 & 3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

In this illustration the network is a 4x2 framework. We realize that for a n x n framework W, at that point a nonzero vector x is the eigenvector of W if:

W **x** = □ **x**

For some scalar. At that point the scalar □ is called an eigenvalue of an, and x is said to be an eigenvector of A comparing to □.

So to discover the eigenvalues of the above substance we figure lattices AA^T and A^TA. As beforehand expressed , the eigenvectors of AA^T make up the sections of U so we can do the accompanying investigation to discover U.

$$AA^T = \begin{bmatrix} 2 & 4 \\ 1 & 3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 & 4 & 0 & 0 \\ 1 & 3 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 20 & 14 & 0 & 0 \\ 14 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} = W$$

Now that we have a n x n matrix we can determine the eigenvalues of the matrix W.

Since W **x** = □ **x** then (W- □I) **x** = 0

$$\begin{bmatrix} 20-\lambda & 14 & 0 & 0 \\ 14 & 10-\lambda & 0 & 0 \\ 0 & 0 & -\lambda & 0 \\ 0 & 0 & 0 & -\lambda \end{bmatrix} \mathbf{x} = (W - \lambda I)\mathbf{x} = 0$$

For a novel arrangement of eigenvalues to determinant of the network (W-□I) must be equivalent to zero. In this way from the arrangement of the trademark condition, |W-□I|=0 we get: □=0, □=0; □ = 15+ö221.5 ~ 29.883; □ = 15-Ö221.5 ~ 0.117 (four eigenvalues since it is a fourth degree polynomial). This esteem can be utilized to decide the eigenvector that can be put in the sections of U. In this manner we acquire the accompanying conditions:

19.883 x1 + 14 x2 = 0

14 x1 + 9.883 x2 = 0

x3 = 0

x4 = 0

After disentangling the initial two conditions we get a proportion which relates the estimation of x1 to x2. The estimations of x1 and x2 are picked with the end goal that the components of the S are the square underlying foundations of the eigen esteems. Along these lines an answer that fulfills the above condition x1 = - 0.58 and x2 = 0.82 and x3 = x4 = 0 (this is the second segment of the U framework).

Substituting the other eigen esteem we acquire:

-9.883 x1 + 14 x2 = 0

14 x1 - 19.883 x2 = 0

x3 = 0

x4 = 0

In this manner an answer that fulfills this arrangement of conditions is x1 = 0.82 and x2 = - 0.58 and x3 = x4 = 0 (this is the main section of the U network). Joining these we acquire:

$$U=\begin{bmatrix} 0.82 & -0.58 & 0 & 0 \\ 0.58 & 0.82 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Similarly A^TA makes up the columns of V so we can do a similar analysis to find the value of V.

$$A^T.A=\begin{bmatrix} 2 & 4 & 0 & 0 \\ 1 & 3 & 0 & 0 \end{bmatrix}\begin{bmatrix} 2 & 4 \\ 1 & 3 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

and similarly we obtain the expression:

$$V=\begin{bmatrix} 0.40 & -0.91 \\ 0.91 & 0.40 \end{bmatrix}$$

At long last as said beforehand the S is the square foundation of the eigen value from AAT or ATA. What's more, can be gotten specifically giving us:

$$S=\begin{bmatrix} 5.47 & 0 \\ 0 & 0.37 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Note that: □1 > □2 > □3 > … which is the thing that the paper was showing by the figure 4 of the Kuruvilla paper. In that paper the qualities were registered and standardized with the end goal that the most astounding solitary esteem was equivalent to 1.

Proof:

$\mathbf{A}=\mathbf{USV}^T$ and $\mathbf{A}^T=\mathbf{VSU}^T$

$\mathbf{A}^T\mathbf{A} = \mathbf{VSU}^T\mathbf{USV}^T$

$\mathbf{A}^T\mathbf{A} = \mathbf{VS}^2\mathbf{V}^T$

$\mathbf{A}^T\mathbf{AV} = \mathbf{VS}^2$

RESULTS

Fig. 2:

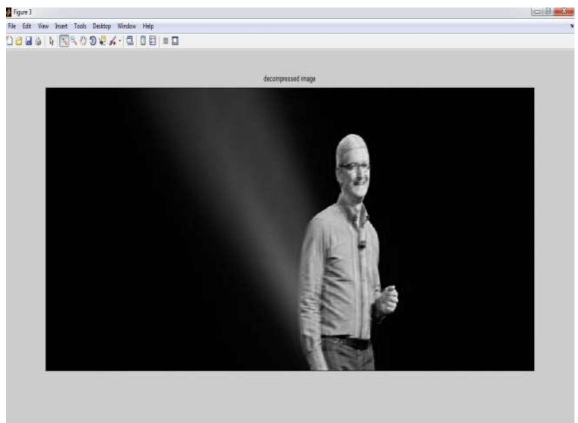


Fig. 3:

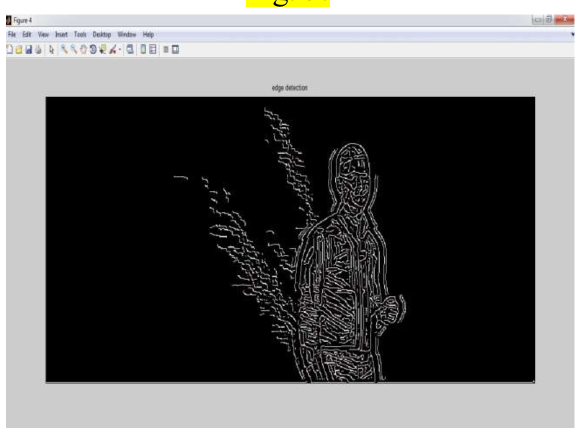


Fig. 4:

I. CONCLUSION

A powerful programmed strategy for lossy picture pressure getting to productive and improved in light of programmed assessment of clamor fluctuation and assurance of the quantization venture for change based coders is planned. It is exhibited that this method gives a decent trade off between packed picture quality and pressure proportion. In addition, it is likewise relevant if unique pictures are sans clamor. The pressure commotion is evaluated in light of quantization steps, and picture earlier models, i.e., a change coefficient earlier model and a picture spatial connection demonstrate. The pressure commotion is evacuated by delicate thresholding the signular estimations of comparative picture fix grids adaptively as indicated by their clamor levels rather than a worldwide clamor level. Broad exploratory outcomes have confirmed that the proposed technique not just fundamentally enhances the nature of packed pictures against the significant existing works, yet in addition benefits PC vision assignments by expelling pressure clamor.

REFERENCES

[1] S. H. Park and D. S. Kim, "Theory of projection onto the narrow quantization constraint set and its application," IEEE Trans. Image Process., vol. 8, no. 10, pp. 1361–1373, Oct. 1999.

[2] G. K. Wallace, "The JPEG still picture compression standard," IEEE Trans. Consum. Electron., vol. 38, no. 1, pp. 18–34, Feb. 1992.

[3] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering," IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

[4] W. Dong, X. Li, D. Zhang, and G. Shi, "Sparsity-based image denoising via dictionary learning and structural clustering," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2011, pp. 457–464.

[5] I. H. Reeve, III, and J. S. Lim, "Reduction of blocking effect in image coding," in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP), vol. 8. Apr. 1983, pp. 1212–1215.

[6] B. Ramamurthi and A. Gersho, "Nonlinear space-variant postprocessing of block coded images," IEEE Trans. Acoust., Speech, Signal Process., vol. 34, no. 5, pp. 1258–1268, Oct. 1986.

[7] S. Minami and A. Zakhor, "An optimization approach for removing blocking effects in transform coding," in Proc. Data Compress. Conf. (DCC), Apr. 1991, p. 442.

[8] A. Norkin et al., "HEVC deblocking filter," IEEE Trans. Circuits Syst. Video Technol., vol. 22, no. 12, pp. 1746–1754, Dec. 2012.

[9] X. Zhang, R. Xiong, S. Ma, and W. Gao, "Adaptive loop filter with temporal prediction," in Proc. Picture Coding Symp. (PCS), May 2012, pp. 437–440.

[10] C.-Y. Tsai et al., "Adaptive loop filtering for video coding," IEEE J. Sel. Topics Signal Process., vol. 7, no. 6, pp. 934–945, Dec. 2013.