A Novel KNN Approach to Implement Inpainting and Compression/Decompression Technique and Get an Optimized Output With the Help of DCT Coefficients

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Abstract
This review work has major focus on images which have cracks and minor distortions in them. This prevents any compression technique to give the best output. Hence there is a need to first remove those distortions from the images before applying compression. A system is proposed, in which K-Nearest Neighbor Algorithm is implemented after the DCT Step, to remove the distortions before compressing it. The neighboring color of the distorted part can be used to merge with the damaged part. So basically, we have to store less color intensities to save the same image without the distorted part which will result in more optimized compression ratio. It will be greatly valuable for viewer perspective.

Keywords
Compression, Inpainting, DCT, KNN

I. Introduction

In this Digital age where bulk of data is getting transferred each and every second, compression methods are a necessity. By being able to compress images to a small fraction of their original size, significant disk space can be spared. Likewise transportation of images starting with one computer then onto the next gets to be simpler and quick [1].

Image compression Algorithms can generally be divided into two types: lossy and lossless. As the name states, when lossless information is decompressed, the ensuing image is indistinguishable to the first. Lossy compression algorithms bring about loss of information and the decompressed image is not precisely the same as the first.

Image inpainting alludes to the issue of filling-in missing regions in an image [2]. Inpainting images with impediment or corruption is an exigent task. The methods mentioned in most of the papers are pixel based, which develop a statistical model from image characteristics. One of the primary burdens of these methodologies is that their viability is constrained by the surrounding pixels of a destroyed part. Subsequently, good performance of these strategies is acquired just when the images have particular consistency. Images in the frequency domain contain sufficient data for image inpainting and can be utilized as a part of data recreation [3], e.g., high frequency indicates image edges or textures, which motivates conducting image inpainting in the frequency domain. In this paper, we propose a novel KNN method which will utilize the DCT coefficients in the frequency domain to remove the distortions. We look for an adequate representation for the functions and utilize the DCT coefficients of this representation to produce an over-complete dictionary. One considers exchanging the pixel-level processing method to the frequency domain for image inpainting utilizing Discrete Cosine Change (DCT).

Existing strategies can be ordered into the accompanying classifications. The principal class concerns diffusion-based methodologies which proliferate level lines (called isophotes) utilizing partial differential equations (PDE) [2, 4-6] or variational systems [7]. The second classification concerns exemplar-based inpainting methods which have been motivated from texture synthesis procedures [8]. These methods exploit image statistical and equivalence toward oneself priors. The texture to be incorporated is adapted by sampling, replicating or by stitching together patches (called exemplar) taken from the known piece of the image. These techniques have developed over recent years with the acquaintance of variations related with the patch processing order [9], to quick search of comparative patches [10], or to the presentation of spatial coherence constraints [11]. An alternate class of methodologies concerns techniques utilizing sparsity priors [12].

As per [13], Instance Based Learning (IBL) algorithms basically stores some or the majority of the training examples and defers any speculation exertion, until another query instance is further anticipated. Actually it applies particular cases or experiences to new circumstances by matching known cases and experiences with the new cases. They can thus construct query specific local models, which endeavor to fit the training samples just in an area around the query instance. This kind of learning method is likewise alluded to as lazy learning method. Since it simply discovers a set of the nearest neighbors and develops a local model focused on them. Examples of the sorts of neighborhood models include Nearest Neighbor (NN), K Nearest Neighbor (KNN) and Locally Weighted Regression (LWR). NN local models just chooses the closest point and utilize its output value. KNN nearby models averages the output according to the nearby points. The KNN system can further be enhanced by weighting each of K Neighbors inversely according to their distance to the query instance.

II. Image Restoration Technique by Nearest Neighbor Method with K>1

In [16], the authors depicted an exemplar-based image inpainting method. The algorithm searches for an approximation of the known pixels of the input patch from its K-NN. This principle is known as neighbor embedding (NE). The paper considers linear regression for enhancing the K-NN search as well as for estimating unknown pixels. Experimental in two applications (loss concealment and object removal) showed superior performances of the LLE-LDNR solution over other neighbor embedding solutions. The results likewise demonstrated further gains when utilizing the proposed improved K-NN search utilizing linear subspace mappings in the context of it.

The main use of K-NN is for regression or classification. Here we are going to do classification. As the name says, to do restoration, we consider the closest neighbors of a pixel. In this paper, we consider for K>1, i.e. an aggregate of neighboring pixel are considered in a filtering window of 8x8. The size of the window can be more than 8x8 as well. In the 2d matrix of image components, every component has a certain correlation with its closest components. With the help of this property, we can write

algorithms to replace a noisy pixel by a value which happens to be the mean of all the closest neighbors. This guarantees a decent level of restoration. The algorithm proposed completes an iterative methodology wherein the mean intensity is discovered from the DCT Coefficients and further substitution of noisy pixel is carried out. Consider an input picture I_m. Given us a chance to characterize a pixel at a position (i,j) in the info picture. Firstly, the likelihood of event of each one neighbor of $I_m(i,j)$ is computed. For a sum of K-neighbors in that window, the mean value is acquired by utilizing the accompanying nearest coefficients.
The value obtained in the above case Eq (1) gives the mean of all neighboring points of a specific pixel.

$$M = \sum_{i=1}^{K} X_i P(X_i) \qquad (1)$$

This gives a value what we call as a ''good pixel value''. Hence we replace the central corrupt pixel by this good pixel value. This guarantees the restoration of the given image by removing the tainted pixels.

III. 8X8 FDCT and IDCT

At the input to the encoder, source image samples are assembled into 8x8 blocks [14], moved from unsigned integers to signed integers by subtracting 128 from each value, and input to the Forward DCT (FDCT). At the output from the decoder, the Inverse DCT (IDCT) yields 8x8 sample blocks to structure the reconstructed picture. The accompanying comparison Eq. (2) and Eq. (3) are the numerical expressions of the 8x8 FDCT and 8x8 IDCT respectively.

$$F(u,v) = \alpha(u)\beta(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\cos\left[\frac{u\pi(2x+1)}{2M}\right]\cos\left[\frac{v\pi(2y+1)}{2N}\right]$$

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where,

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{M}} & ,if\ u=0 \\ \sqrt{\frac{2}{M}} & ,otherwise \end{cases}$$

and,

$$F(x,y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} \alpha(u)\beta(v) f(u,v) \cos\left[\frac{u\pi(2x+1)}{2M}\right]\cos\left[\frac{v\pi(2y+1)}{2N}\right] \qquad (3)$$

The discrete cosine transform is the premise for the JPEG compression standard. It is an exceptional instance of the Fourier transform in which the sine components are wiped out. For JPEG, a two-dimensional DCT algorithm is utilized which is basically the one-dimensional variant evaluated twice. Our desire is that, over a 8x8 block, the progressions in the parts of the (Y, Cb, Cr) vector are fairly rich. DCT is worked two dimensionally considering 8 x 8 blocks of pixels. The resultant information set is a 8 by 8 block of frequency space components, the coefficients scaling the arrangement cosine terms, known as basis functions. The Principal component at column 0 and row 0, is known as the DC term, average frequency value of the entire block. The spatial frequencies are represented in the other 63 terms, which represent the spatial frequencies that form the input pixel block, by scaling the cosine terms inside the series.

III. Objective of the Study

The two main objective of this paper is inpainting and compressing images with noise(after denoising/inpainting). As discussed in the introduction, its preferable that the image is first removed from any distortions before applying compression to get a more optimized output.

IV. Proposed Approach

1. Obtain image (having cracks and minor distortions).
2. Divide it into 8x8 matrix components.
3. Convert RGB to Grayscale.
4. Convert RGB to YCbCr component.
5. Convert the grayscale matrix to Black and White (logical class) and save the positions of 1(luminance) from the matrix.
6. Apply DCT to the YCbCr matrix obtained from step 4.
7. Apply KNN Algorithm to the positions obtained from step 5, in the DCT Coefficients.
8. Apply Quantization to compress the data.
9. Apply Variable Length Coding which includes Zigzag filtering and Run-Length Encoding or Huffman Encoding.

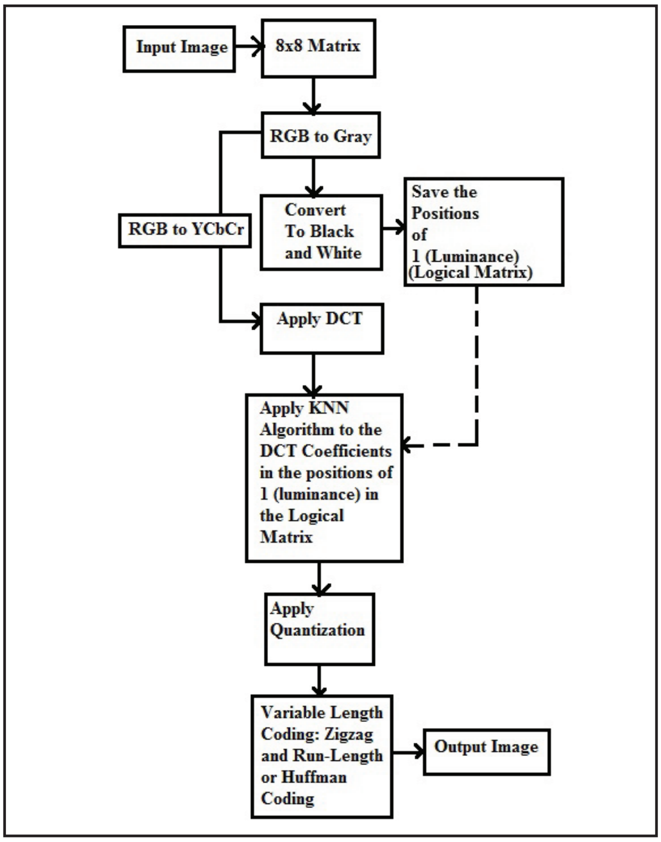

Fig. 1:

Fig: 1 describes the steps that will be followed in our approach. The image is converted into Black and White to retrieve the positions of cracks/distortions. In this, only luminance is shown with 1(the cracks and distortions) in the matrix. Rest every chroma component is 0. This is known as logical class

V. Conclusion

This paper analyzes coding algorithm of JPEG image and proposes a K-Nearest Neighbor (KNN) approach to perform inpainting in the DCT Coefficients to get a more optimized compression ratio. The proposed methodology is expected to outperform the compression ratio of the Baseline JPEG Algorithm dealing with images having cracks and distortions. The reason behind this is plain and simple. Images having distortions will have anomalies in the distorted parts which will contribute to the size of the image. If those distortions are removed before compression, the output will be more optimized.

The proposed methodology is expected to give a good PSNR value compared to the output of JPEG Baseline Algorithm. The output image from the system is expected to be visually more attractive to the Human eyes because of the removal of noise that were present before compressing the image.

A conventional image quality index is the peak signal-to-noise ratio (PSNR), which is the ratio of the squared image intensity dynamic range to the mean squared difference of the original and distorted images [15]. It is widely used for the estimation of quality in lossy image compression algorithms. This index is popular for its simplicity; however, it loses its advantages compared with natural human perception [20].

$$PSNR = 10 \times log10\left(\frac{(2^n-1)^2}{RMSE}\right) \quad (4)$$

where,

$$\text{RMSE} = \frac{1}{H \times W}\sum_{i=1}^{H}\sum_{j=1}^{W}[I(i,j) - K(i,j)]^2 \quad (5)$$

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