

Improving the Image Quality by Using the DCT Coefficients

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ABSTRACT:

The reason for us to opt for this paper is to enhance the vision clarity, to enrich its perceptive view. Direct visual perception computes the conscious representation with vivid color and detail in shadows, and with resistance to spectral shifts in the scene illuminant. Observation and recorded color images of the same scenes are often strikingly different because humanThis paper presents a new technique for color enhancement in the compressed domain. The proposed technique is simple but more effective than some of the existing techniques reported earlier. The novelty lies in this case in its treatment of the chromatic components, while previous techniques treated onlythe luminance component. This is simplified with the usage luminance component because it adjusts the brightness alone.Thus results of all previous techniques along with that of the proposed one are compared with respect to those obtained by applying a spatial domain color enhancement technique that appears to provide very good enhancement. The proposed technique, computationally more efficient than the spatialdomain based method, is found to provide better enhancement compared to other compressed domain based approaches.

Keywords:

Color Image Processing, Discrete Cosine Transform, Image Enhancement, Primary and secondary color, Luminance Component, Video Compression.

I. Introduction:

An image becomes digital when it is sampled and quantized into a form which can be understood by a computer. It is tured into a long string of on/off signals.

The smallest element of a conventional photograph is a piece of grain. The equivalent digital picture is a pixel. The pix part of this word is from picture, the el from element. Join them together and ou have pixel.Digitizing an image is like overlaying a very fine wire netting over a scene, analyzing the color and brightness seen through each part of the mesh, and then noting down the values in correct order in a huge list [1,3]. The image is very clear when the number of pixels is high. An important concept is that while monitor screen picture element or pixel does have a physical size, an image pixel does not. The monitor screen's pixel size is fixed forever when the screen is manufactured at the factory just as its counterpart, the grain is silver halide photography is fixed in size when the film is manufactured. On the other hand, a digital image pixel has no physical size until you give it one. A pixel is simply a mathematical definition inside the computer.

Its size can be changed to suit our need. Color image processing is divided into two major areas: full-color and pseudo color processing. In the first category, the images in question typically are acquired with a full-color sensor, such as a color TV camera or color scanner. In the second category, the problem is one of assigning a color to particular monochrome intensity or range of intensities. Until relatively recently, most digital color image processing was done at the pseudo color level. The use of color in image processing is motivated by two principal factors. First, color is a powerful descriptor that often simplifies object identification and extraction from a scene.Second, humans can discern thousands of color shades and intensities, compared to about only two dozen shades of gray.This second factor is particularly important in manual (i.e., when performed by humans) image analysis. There are two types of colors they are

- 1.Primary colors
- 2.Secondary colors

II. Proposed Algorithm:

Every image is on the bases of color, contrast and brightness, these three primary elements are altered in order to obtain enhanced image. Thus direct observation and recorded color images of the same scenes are often strikingly different because human visual perception computes the conscious representation with vivid color and detail in shadows, and with resistance to spectral shifts in the scene illuminant [2,4].

1. Read the Image.
2. Resize that image for applying DCT Compression.
3. Convert into ycbcr color space
4. Convert luminance part of the input image into vector.
5. Calculate the scaling coefficient from this image.
6. Apply DCT for all three color spaces.
7. Convert image into vector for this compressed images.
8. Apply the scaling coefficient into compressed image in all three color spaces.
- I. For brightness Scale Only DC Coefficients.
- II. For contrast Scale DC and AC Coefficients.
- III. For color Scale DC and AC Coefficients using function (use all three colors Information)
9. Convert vector into image.
10. Apply inverse DCT.
11. Convert into RGB color space.

A. Resizing of the image:

The most popular image and video compression methods such as JPEG, MPEG use transform domain techniques and in particular the Discrete Cosine Transform (DCT). One application for such images or video sequences is resizing.

Resizing is extensively used to meet the requirements of a specific system, to satisfy user's interests, or to correct spatial distortions [3]. However, a major difficulty encountered when resizing such media is the high computational complexity and the loss of quality caused by the decompression and compression.

B. Properties of resizing

- Real (unlike DFT)
- Separable
- Efficiently calculated $-O(n \cdot \log)$
- The (0,0) element (top-left) is the DC component

Used in JPEG and MPEG. DCT has a strong "energy compaction" property: most of the signal information tends to be concentrated in a few low-frequency components

C. YCbCr

YCbCr or Y'CbCr is a family of color space used as a part of the A New Technique for Enhancement of Color Images by Scaling the Discrete Cosine Transform Coefficients color image pipeline in video and digital photography systems. Y is the luma component and CB and CR are the blue-difference and red-difference chroma components. Y' (with prime) is distinguished from Y which is luminance; meaning that light intensity is non-linearly encoded using gamma. Y image is essentially a greyscale copy of the main image. Y CbCr is not an absolute color space; it is a way of encoding RGB information. The actual color displayed depends on the actual RGB colorants used to display the signal. Therefore a value expressed as YCbCr is only predictable if standard RGB colorants. YCbCr and YCbCr are a practical approximation to color processing and perceptual uniformity, where the primary colours corresponding roughly to Red, Green and Blue are processed into perceptually meaningful information [4,9]. By doing this, subsequent image/video processing, transmission and storage can do operations and introduce errors in perceptually meaningful ways. YCbCr is used to separate out a luma signal (Y) that can be stored with high resolution or transmitted at high bandwidth, and two chroma components (CB and CR) that can be bandwidth-reduced, subsampled, compressed, or otherwise treated separately for improved system efficiency.

D. Discrete cosine transforms (DCT):

DCT and DST is the fastest transform in the existing transforms. But DCT is more commonly used in image compression algorithms compared to DST. Because it reduces the number of computational complexity. The 2-D image of the DCT equation is given by $\{x(m,n), 0 \leq m \leq N-1, 0 \leq n \leq N-1\}$ The coefficient $C(0,0)$ is the DC coefficient and the remaining are the AC coefficients for the block.

E. Inverse discrete cosine transforms (IDCT):

The 2-D image of the IDCT equation is given by $\{c(k,l), 0 \leq k \leq N-1, 0 \leq l \leq N-1\}$ Here also the coefficient $X(0,0)$ is the DC coefficient and the remaining are the AC coefficients for the block. Generation of Many image and video compression schemes perform the discrete cosine transform (DCT) to represent image data in frequency space. An analysis of a broad suite of images confirms previous finding that a Laplacian distribution can be used to model the luminance AC coefficients [7]. This model is expanded and applied to color space (Cr/Cb) coefficients.

In MPEG, the DCT is used to code interframe prediction error terms. The distribution of these coefficients is explored. Finally, the distribution model is applied to improve dynamic. Many digital image and video compression schemes use a blockbased Discrete Cosine Transform (DCT) as the transform coding. In particular JPEG and MPEG use the DCT to concentrate image information. Image compression systems often divide each image into multiple planes, one for luminance (brightness) and two for color (for example chrominance-red and chrominanceblue). The images are also spatially divided into blocks, usually 8x8 pixels. The DCT is applied to each block in each plane and the results are quantized and run-length encoded (with additional Huffman or arithmetic coding).

III. Adjustment of Local Background Brightness

Brightness is a subjective descriptor that is practically impossible to measure it embodies de achromatic notion of intensity and it is one of the key factors in describing color sensation.

In adjusting the local background illumination, the DC coefficient of a block is used. The DC value gives the mean of the brightness distribution of the block. This adjustment may be performed by mapping the brightness values to a value in the desired range. This function should be monotonic in the given range [5,6]. Fig.1: Encoding and decoding RGB information process Let us denote the maximum brightness value of the image as I_{max} (which may be available from the header of the compressed stream). Their functional forms are given below, shown at the bottom of the next page. The reasons for choosing these functions are as follows: i) they have been employed earlier in developing image enhancement algorithms, and ii) there is no single function which has been found to provide the best performance for every image. Our objective here is to observe the performances of our proposed algorithm with different choices of these mapping functions. There are also other advantages for using each of the above functions.

A. Preservation of local contrast:

Contrast, which we define as the difference in intensity between the highest and the lowest intensity levels in an image. The concept of contrast simultaneous is related entirely to the perceived brightness does not depend simply on its intensity; they appear to the eye to become darker as the background gets lighter [6 - 8]. The basic idea of our algorithm is to filter the image by manipulating the DCT coefficients according to the contrast measure defined. The proposed algorithm has the following advantages: 1) the algorithm does not affect the compressibility of the original image; 2) given a majority of zero-valued DCT coefficients (after quantization), the algorithm expense is relatively low; and 3) the proposed image enhancement algorithm is applicable to any DCT-based image compression standard, such as JPEG, MPEG.

B. Preservation of color:

By extensive analysis with several video sequences, we observed that the statistical distribution of the color is in typical applications is closer to the enhancement. These techniques only change the luminance component (Y) and keep the chrominance components (Cb and Cr respectively) unaltered. Though in the Y - Cb - Cr color space the chrominance components are

de-correlated better than that in the R - G - B color space, the increasing values in the Y component usually tend to de-saturate the colors. Typically one may observe from the conversion matrix for going from the Y - Cb - Cr space to the R - G - B space, for $G > R$ and $G > B$ increasing Y while keeping Cb and Cr unchanged reduces both the (R/G) and (B/G) factors [3,4]. This is why we believe that the chromatic components should be also processed for preserving the colors.

C. Algorithm for color enhancement by scaling (CES)

Input : Y , U , V : DCTs of three components of a block.
Input Parameters: f(x) (the mapping function) , lmax , Bmax , κ , σ_{thresh} , N(Block size).

Output: \tilde{U} , \tilde{V} , \tilde{Y} .

1. Compute σ and μ .
2. If ($\sigma > \sigma_{\text{thresh}}$),
 - 2a. Decompose into $(N/2) \times (N/2)$ DCT sub-blocks,
 - 2b. For each block apply similar computations as described in Steps 3 through 5, and
 - 2c. Combine 4 of these $(N/2) \times (N/2)$ blocks into a single $N \times N$ DCT block and return.
3. Compute the enhancement factor (κ) as follows:
 - 3a. $\kappa = (f(Y(0,0)/N.lmax)) / (Y(0,0)/N.lmax)$,
 - 3b. $\kappa = \min(\kappa, (Bmax / \mu + \kappa \sigma))$ and
 - 3c. $\kappa = \max(\kappa, 1)$
4. Scale the coefficients:
 - 4a. $= \kappa Y$, and
 - 4b. Apply (11) and (12) on U and V for preserving colors. removal

IV. Comparison of Results with the Previous Approach:

We have compared the performance of the proposed approach with that of three existing DCT domain color enhancement techniques, namely alpha-rooting, multicontrast enhancement technique, multicontrast enhancement coupled with dynamic range compression and contrast enhanced by scaling [5 - 7].

A. Alpha Rooting (Ar):

The computation according to Alpha rooting it requires 1 multiplication and 1 exponentiation operation. Hence, the computational complexity can be expressed as $1M + 1E$ per pixel.

B. Multicontrast Enhancement (MCE):

Computation of the cumulative energies for both enhanced and original blocks requires 126 additions (ignoring the cost of absolute operations). For computing H_n , $1 \leq n \leq 14$, 14 divisions are required and finally the scaling of the AC coefficients requires two multiplications each. The total number of operations for each block is thus 140 multiplications and 126 additions.

C. Multicontrast Enhancement with Dynamic Range Compression (MCEDRC):

As this technique L2 uses norm, the computation of cumulative energies becomes more expensive than the previous technique. In this case, the number of operations is 128 Multiplications and 126 Additions [7]. In addition, the dynamic range compression requires the computation of the function (x) with 2 exponentiation and 2 addition operations. Considering all other factors similar to the previous.

D. Contrast Enhancement by Scaling (CES):

In this algorithm, the scaling of the coefficients by a constant for each component is the major computational task. This would require 192 multiplications and four additions. The additions are necessary for translating (and retranslating back) the DC coefficients of the Cb and Cr components [9]. Computation of the scaling factor depends on the type of functions used.

V. Simulations and Results



(a)

Fig a: ORIGINAL IMAGE



(b)

Fig b: ENHANCED IMAGES

VI. CONCLUSION:

The field of image processing has been growing at a very fast pace. The day to day emerging technology requires more and more revolution and evolution in the image processing field. The well known saying “A picture says a thousand words” can be taken as the main motive behind the need of image processing. The proposed denoising technique can provide a good platform for further research work in this respect. This work can be further enhanced to denoise the other type of images, as well, like RGB, Indexed and Binary images. It will provide a good add on to the already existing denoising techniques used for denoising these images. Moreover, for future work we can train our algorithm using various AI techniques like fuzzy logic or neural network, in order to attain the best output without performing calculations for each and every combination. Use of AI techniques will lead to the optimal solution directly, with more efficiency and less tedious work.

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