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Research Article

DCT and Fuzzy based Analysis of Quantization Effects for JPEG Image

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Abstract

The objective of this paper is to find the effects of quantization matrices (10%, 50%, 90%) on Discrete cosine transform and Fuzzy logic (without quantization) using different resolution (256X256, 512X512) of an JPEG image. After comparison of DCT and fuzzy logic separately, the effect of quantization matrices is tested by linking DCT and fuzzy logic using different resolution of an JPEG image. In recent years, many researchers have applied the fuzzy logic to develop new techniques for contrast improvement. Fuzzy logic is a well known rather simple approach with good visual results, but proposed fuzzy operation algorithm is default nonlinear. Here proposed algorithm is a default nonlinear thus not straight forward applicable on the JPEG bit stream, it is possible when the right combination is found. The processing is much faster, due to the reduced number of co-efficient, because the majority of the coefficient in the DCT domain is zero after quantization. Discrete cosine transform is a technique which converts signal to elementary frequency components and is mainly used for image compression. Image compression has become important as storage or transmission of images requires large amount of bandwidth. Performance measurement is carried out in terms of Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The proposed work is designed using MATLAB 7.10.

Keywords: *DCT, 2D DCT, Fuzzy logic, Fuzzy Intensification Operator, Image Compression, Quantization, MSE, PSNR.*

1. Introduction

Discrete cosine transform is a technique which converts signal to elementary frequency components and is mainly used for image compression. A DCT (Rafel C.Gonzalez et al .1993) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. The JPEG process is a widely used form of lossy image compression that centers on the DCT. The DCT works separating images into parts of differing frequencies. During a step called quantization where part of compression actually occurs, the less important frequencies are discarded, hence the use of the term lossy''. Then, only the important frequencies that remain are used retrieve the image in the decompression process. As a result, reconstructed images contain some distortion . A remarkable and highly useful feature of the JPEG process is that in this step (quantization), varying levels of image compression and quality are obtainable through selection of specific quantization matrices. This enables the user to decide on quality levels ranging from 1 to100, where 1 gives the poorest image quality and highest compression, while 100 gives the best quality and lowest compression. As a result, the quality/compression ratio can be tailored to suit different needs.

Subjective experiments involving the human visual system have resulted in the JPEG standard quantization matrix. With a quality level of 50, this matrix renders both high compression and excellent decompressed image quality.

$$Q_{50} = \begin{pmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{pmatrix}$$

If, however, another level of quality and compression is desired, scalar multiples of the JPEG standard quantization matrix may be used. For a quality level greater than 50 (less compression, higher image quality), the standard

$$Q_{10} = \begin{pmatrix} 80 & 60 & 50 & 80 & 120 & 200 & 255 & 255 \\ 55 & 60 & 70 & 95 & 130 & 255 & 255 & 255 \\ 70 & 65 & 80 & 120 & 200 & 255 & 255 & 255 \\ 70 & 85 & 110 & 145 & 255 & 255 & 255 & 255 \\ 90 & 110 & 185 & 255 & 255 & 255 & 255 & 255 \\ 120 & 175 & 255 & 255 & 255 & 255 & 255 & 255 \\ 245 & 255 & 255 & 255 & 255 & 255 & 255 & 255 \\ 255 & 255 & 255 & 255 & 255 & 255 & 255 & 255 \end{pmatrix}$$

quantization matrix is multiplied by (100-quality level)/50. The scaled quantization matrix is then rounded and clipped to have positive integer values ranging from 1 to

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255. For example, the following quantization matrices yield quality levels of 10 and 90.

$$Q_{90}=\begin{pmatrix}3&2&2&3&5&8&10&12\\2&2&3&4&5&12&12&11\\3&3&3&5&8&11&14&11\\3&3&4&6&10&17&16&12\\4&4&7&11&14&22&21&15\\5&7&11&13&16&12&23&18\\10&13&16&17&21&24&24&21\\14&18&19&20&22&20&20&20\end{pmatrix}$$

Quantization is achieved by dividing each element in the transformed image matrix D by corresponding element in the quantization matrix, and then rounding to the nearest integer value. For the following step, quantization matrix Q_{50} is used

$$C_{i,j}=round\left(\frac{D_{i,j}}{Q_{i,j}}\right)$$

$$C=\begin{pmatrix}10&4&2&5&1&0&0&0\\3&9&1&2&1&0&0&0\\-7&-5&1&-2&-1&0&0&0\\-3&-5&0&-1&0&0&0&0\\-2&1&0&0&0&0&0&0\\0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&0\end{pmatrix}$$

Recall that the coefficients situated near the upper-left corner correspond to the lower frequencies to which the human eye is most sensitive of the image block. In addition, the zeros represent the less important, higher frequencies that have been discarded, giving rise to the lossy part of compression. As mentioned earlier, only the remaining nonzero coefficients will be used to reconstruct the image. It is also interesting to note the effect of different quantization matrices use of Q_{10} would give C significantly more zeros, while Q_{90} would result in very few zeros.

The JPEG method is used for both color and black and white images. Importance of image compression increases with advancing communication technology (Rafel C. Gonzalez et al.1993). The amount of data associated with visual information is so large that its storage requires enormous storage capacity. The storage and transmission of such data require large capacity and bandwidth, which could be very expensive. Image data compression techniques (Agaian S. S, et al 2007) are concerned with reduction of the number of bits required to storage or transmit images without any appreciable loss of information. Compression is achieved by exploiting the redundancy (Rafael C. Gonzalez et al .1993). Images stored in JPEG format, it is recommended to process them directly in the compressed domain, in order to reduce the time needed to process data. Fuzzy logic (Camelia Florea et al. 2009, Cmelia Popa et al. 2007) is a useful technique in image contrast enhancement. It is provided by the application of fuzzy sets theory and fuzzy inference systems. The fuzzy sets theory's foundation was set by Prof. Zadeh in 1965, followed later on by the fuzzy logic basis, established in 1973 since then the applications of fuzzy sets theory and fuzzy logic to scientific computing are extremely vast and still continue to evolve along with other modern algorithms in the area of soft computing. In short the essence of fuzzy thinking (Camelia Florea et al. 2009), which makes it such an appealing tool for reformulation and implementation of various data processing algorithms, one can see fuzzy variables, fuzzy logic and fuzzy reasoning as the extension of the crisp (binary) reasoning to the infinite valued logic case, which allows for a mathematical representation of the imprecision and uncertainty in the definition of terms typical to the human like thinking and dually for a certain granularity in defining otherwise precise terms in a more approximate flexible manner .

In linguistics (Timothy J. Ross 2005), fundamental atomic terms are often modified with adjectives (nouns) or adverbs (verbs) like very, low, slight, more or less, fairly, slightly, almost, barely, mostly, roughly, approximately, and so many more that it would be difficult to list them all . We will call these modifiers linguistic hedges. Using fuzzy sets as the calculus of interpretation, these linguistic hedges have the effect of modifying the membership function for a basic atomic term. The basic linguistic atom α is subject it to some hedges. Define

$$\alpha=\int_Y^{\cdot}\frac{[\mu_\alpha(y)]^2}{y} \quad \text{then}$$

$$Very\ \alpha=\alpha^2=\int_Y^{\cdot}\frac{[\mu_\alpha(y)]^2}{y} \qquad (1)$$

$$Very,very\alpha=\alpha^4 \qquad (2)$$

$$Plus\alpha=\alpha^{1.25} \qquad (3)$$

$$Slightly\ \alpha=\sqrt{\alpha}=\int_Y^{\cdot}\frac{[\mu_\alpha(y)]^{0.5}}{y} \qquad (4)$$

$$Minus\ \alpha=\alpha^{0.75} \qquad (5)$$

The expressions shown in Eqs. (1) - (3) are linguistic hedges known as concentrations. Concentrations tend to concentrate the elements of a fuzzy set by reducing the degree of membership of all elements that are only partly in the set. The less an element is in a set (i.e., the lower its original membership value), the more it is reduced in membership through concentration. For example, by using Eq.(1) for the hedge very, a membership value of 0.9 is reduced by 10% to a value of 0.81, but a membership value of 0.1 is reduced by an order of magnitude to 0.01. This decrease is simply a manifestation of the properties of the membership value itself for $0\leq\mu\leq 1$, then $\mu\geq\mu^2$. Alternatively the expressions given in Eqs. (4) and (5) are linguistic hedges known as dilations (or dilutions in some publications). Dilations stretch or dilate a fuzzy set by increasing the membership of elements that are partly in the set. For example using Eq.(4) for the hedge slightly, a membership value of 0.81 is increased by 11% to a value of 0.9, whereas a membership value of 0.01 is increased by an order of magnitude to 0.1.

Another operation on linguistic fuzzy sets is known as intensification. This operation acts in a combination of concentration and dilation. It increases the degree of membership of those elements in the set with original membership values greater than 0.5 and it decreases the degree of membership of those elements in the set with original membership values less than 0.5. This also has the effects of making the boundaries of the membership function steeper.

Intensification (Camelia Florea et al. 2009) can be expressed by numerous algorithms, one of which proposed by Zadeh in 1972 is

$$\text{intensify } \alpha = \begin{cases} 2\mu_\alpha^2(y) & for\ 0 \le \mu_\alpha(y) \le 0.5 \\ 1 - 2[1-\mu_\alpha(y)]^2 & for\ 0.5 \le \mu_\alpha(y) \le 1 \end{cases} \quad (6)$$

Intensification increases the contrast between the elements of the set that have more than half membership and those that have less than half membership.

2. Methodology

A. Image processing using the compressed domain

This method is to test how different quantization matrices cause effects on DCT for different resolution of an JPEG image. Steps are explained as below

1. First read the input image, here lena images of different resolution (256x256, 512x512) is used for image processing.
2. The images is divided into 8X8 blocks, and each block is individually processed. A DCT is applied on each block providing the DCT coefficient which is quantized by different matrices. Many small coefficients, usually high frequency ones, are quantized to zero. During a step called quantization where part of compression actually occurs, the less important frequencies are discarded, hence the use of the term lossy''. Here quantization is done using different matrices i.e., 10%, 50%, 90%. Then, only the important frequencies that remain are used retrieve the image in the decompression process. As a result, reconstructed images contain some distortion.

B. Image processing using the intensification operator

Here Fuzzy Intensification operator is used as algorithm. This method shows how JPEG image effected by applying fuzzy logic and without applying different quantization matrices. Steps are explained as below

1. First read the input image, here lena images of different resolution (256x256, 512x512) are used for image processing.
2. Then images are normalized. Normalization is a process that changes the range of pixel intensity values. In normalization every element (value) is divided by maximum value. It ranges from 0 to1.
3. Then membership function rule is applied i.e

$$B'(l) = INT(B(l)) = \begin{cases} 2 \cdot B^2(l), & \text{if } 0 \le B(l) \le 0.5 \\ 1 - 2\cdot(1 - B(l))^2 & \text{if } 0.5 \le B(l) \le 1 \end{cases} \quad (7)$$

4. At last every value is multiplied by maximum value i.e., denormalization is done to get enhanced image. Here quantization using different matrices is not possible.

C. Image processing through intensification operator in the compressed domain.

This method is to link DCT and proposed algorithm (Fuzzy Intensification) and to find how different quantization matrices effects on this method. Steps are explained as below

1 .First read the input image, here lena images of different resolution (256x256, 512x512) is used for image processing.
2. Fuzzification is described by

$$B(l) = a \cdot l + b \quad (8)$$

For any l in the image

The value of a is calculated by

$$a = \frac{0.5}{\max\{(l_{thd} - l_{min}), (l_{Max} - l_{thd})\}}$$

The value of the second parameter b is obtain from B (l_{thd})

B (l_{thd}) = 0.5 $\Longrightarrow$ a· l_{thd} + b= 0.5 $\Longrightarrow$ b = 0.5 - a· l_{thd}

l_m= 0, l_M= 255, l_{thd}= 128 this value is considered by seeing fig1.b

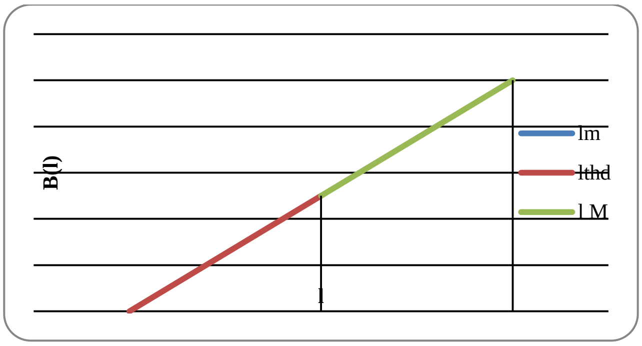

Fig 1.a. The linear slope

3. Defuzzification is given by B'(l)

$$B'(l) = INT(B(l)) = \begin{cases} 2\cdot(a\cdot l + b)^2, & \text{if } 0 \le (a\cdot l + b) \le 0.5 \\ 1 - 2\cdot(-a\cdot l + 1 - b),^2 & \text{if } 0 \le (a\cdot l + b) \le 0.5 \end{cases} \quad (9)$$

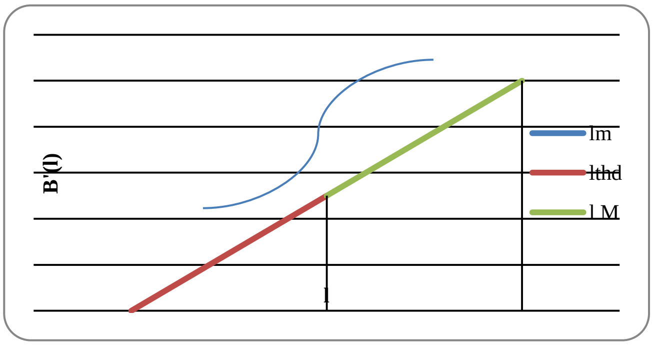

Fig. 1. b. The fuzzy intensification operator

4. Equation (9) can be written in a form more suitable for the identification of the needed operation,to be performed in the compressed domain as

$$B'(l) = \begin{cases} 2\cdot a^2\cdot l^2 + 4\cdot a\cdot b\cdot l + 2\cdot b^2, & if\ 0 \le (a\cdot l + b) \le 0.5 \\ -2\cdot a^2\cdot l^2 + 4\cdot a\cdot(1-b)\cdot l + 1 - 2\cdot(1-b)^2, & if\ 0.5 \le (a\cdot l + b) \le 1 \end{cases} \quad (10)$$

5. The resulting grey level , $l' = fint\ (l) = B^{-1}(B\ (l)\ )$, will be

$$f_{int} = \frac{B'(l) - b}{a}$$

$$f_{int}(l) = \begin{cases} 2\cdot a\cdot l^2 + 4\cdot b\cdot l + \frac{2\cdot b^2 - b}{a}, & \text{if } 0 \le (a\cdot l + b) \le 0.5 \\ -2\cdot a\cdot l^2 + 4\cdot(1-b)\cdot l + \frac{1-2\cdot(1-b)^2 - b}{a}, & \text{if } 0.5 \le (a\cdot l + b) \le 1 \end{cases} \quad (11)$$

The threshold for the fuzzy algorithm in the compressed domain should change to its equivalent in the range [-128,127] denoted here by $DC_{thd} = l_{thd} - 128$.Since the value of l_{thd} can be computed from the membership function B as:

$$a\cdot l_{thd} + b = 0.5 \Longrightarrow l_{thd} = \frac{0.5-b}{a}$$

$$l_{thd} - 128 = \frac{0.5-b}{a} - 128$$

The expression of DC_{thd} becomes

$$DC_{thd} = \frac{0.5-b}{a} - 128 \quad (12)$$

6. In the compressed domain all the grey values are scaled symmetrically towards 0,which means ,that we should express all the terms in equation (11) in terms of these translated grey levels

$$l_t = (l - 128) \Longrightarrow l = l_t + 128$$

$$l_t^2 = (l-128)^2 \Longrightarrow l^2 + 2\cdot 128.\, l_t - 128^2 \quad (13)$$

replacing the expression of l and l^2 from equation (13) in equation (11) ,we will have the following resulting form of the intensification

$$f_{int}\ (l_t) = \begin{cases} 2\cdot a\cdot l_t^2 + (4\cdot a\cdot 128 + 4\cdot b)\cdot l_t \\ \quad + \left(2\cdot a\cdot 128^2 + 4\cdot b\cdot 128 + \frac{2\cdot b^2 - b}{a} - 128\right) \\ \text{if } 0 \le (a\cdot l + b) \le 0.5 \\ -2\cdot a\cdot l_t^2 + (-4\cdot a\cdot 128 + 4\cdot(1-b))\cdot l_t \\ \quad + \left(-2\cdot a\cdot 128^2 + 4\cdot(1-b)\cdot 128 + \frac{1-2\cdot(1-b)^2 - b}{a} - 128\right) \\ \text{if } 0.5 \le (a\cdot l + b) \le 1 \end{cases} \quad (14)$$

In order to implement the fuzzy algorithm in the compressed domain, linear operations and nonlinear operations are necessary. Here DCT of the 8x8 block should be squared luminance. We denote DCT matrix by $u_{dct,sq}$[8x8].This is done for different quantization matrices.

7. Performance measurement is carried out in terms of Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) for 3 methods of different quantization matrices of different resolution of an image.

3.Result

A. Image processing using the compressed domain

i. .for 256x256 image

Fig 2a: Original image of size 256x256 , b:Reconstructed image .Using 10% quantization matrix.

Fig 3a: Original image of size 256x256, b:Reconstructed image. Using 50% quantization matrix.

Fig 4a: Original image of size 256x256, b:Reconstructed image. Using 90% quantization matrix.

ii. for 512x512

Fig 5a: Original image of size 512x512, b:Reconstructed image. Using 10% quantization matrix.

Fig 6a: Original image of size 512x512, b:Reconstructed image .Using 50% quantization matrix.

Fig 2a,b, 3a,b and 4a,b shows the input image and reconstructed image of size 256X256 . Fig 5a,b,6a,b and 7a,b shows the input image and reconstructed image of size 512X512. Here performance is observed by MSE and PSNR value as shown in Table.1

Fig 7a: Original image of size 512x512, b:Reconstructed image Using 90% quantization matrix.

Table.1: Results for different quantization and resolution of a JPEG image

JPEG Image	Resolution	Quantization matrices	MSE	PSNR (dB)
lena	256X256	10%	0.0245	64.26
		50%	0.003	73.42
		90%	20.84	78.55
	512X512	10%	0.0139	72.74
		50%	0.016	82.28
		90%	8.17	87.48

A. Image processing using the intensification operator

i.for 256x256

Fig 8a: Original image of size 256x256, b:Denormalized image.

]ii.for 512x512

Fig 9a: Original image of size 512x512, b:Denormalized image

Table.2: Results for different quantization and resolution of an JPEG image

Image	Resolution	Quantization matrices	MSE	PSNR (dB)
lena	256X256	10%	10.4	13.81
		50%	10.4	13.81
		90%	10.4	13.81
	512X512	10%	11.45	19.24
		50%	11.45	19.24
		90%	11.45	19.24

Fig 8a,b and 9a,b shows the input and denormalized image of size 256x256 and 512x512. Here performance is observed by MSE and PSNR value as shown in Table.2

C. Image processing through intensification operator in the compressed domain.

i. .for 256x256 image

Fig 10a: Original image of size 256x256, b:.Defuzzified image.Using 10% quantization matrix.

Fig 11a: Original image of size 256x256,b:Defuzzified image . Using 50% quantization matrix.

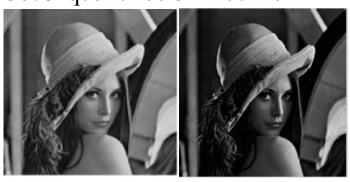

Fig 12a: Original image of size 256x256, b:Defuzzified image . Using 90% quantization matrix.

ii.for 512x512

Fig 13a: Original image of size 512x512, b:Defuzzified image. Using 10% quantization matrix.

Fig 14a: Original image of size 512x512, b:Defuzzified image. Using 50% quantization matrix.

Fig 15a: Original image of size 512x512, b:Defuzzified image. Using 90% quantization matrix.

Fig 9a,b, 10a,b, 11a,b,12a,b 13a ,b,14a,b shows the input and output defuzzified image of an 256x256 and 512x512 image for different quantization matrices (10%,50%90%). . Here performance is observed by MSE and PSNR value as shown in Table.3

Table.3: Results for different quantization and resolution of an JPEG image

Image	Resolution	Quantization matrices	MSE	PSNR (dB)
lena	256X256	10%	10.4	13.81
		50%	10.4	13.81
		90%	10.4	13.81
	512X512	10%	11.45	19.24
		50%	11.45	19.24
		90%	11.45	19.24

Conclusion

This paper has introduced the effects of quantization matrices on Discrete cosine transform and Fuzzy logic using different resolution of an image. This paper tells about how different quantization matrices effects DCT and fuzzy intensification algorithm for different resolution. We see that PSNR value of images in DCT varies for different quantization matrices but when we combine Fuzzy logic and DCT PSNR does not varies and here we will get enhanced, high quality and compressed image. Such an algorithm has been proven (by experiments) to significantly increase the computational efficiency in image processing algorithms applied to a JPEG image (preserving the visual quality of the processing result).The computational efficiency is high since by the strategy, one can avoid the decompression and recompression prior and after the processing. This guarantees the optimal quality at minimum computational cost.

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