The Effect of Using Different Color Spaces On Haar Wavelet Transformed Images

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Abstract:
Wavelets provide a powerful set of tools for handling fundamental problems in science and engineering, such as image compression, edge detection and fingerprint compression and image de-noising. This paper applies the Haar wavelet on various types of images with different sizes after converting the colored image (RGB) to grayscale Image (LC color space which is based on *luminance* (L) and *chrominance* (C) values) like YIQ, YUV and YC_bC_r color spaces to see how it affects on the quality based on the PSNR value. This type of transform gives some degradation in quality, so this research helps the researchers to decide the best LC color space that have to be used when compressing images with Haar wavelet transform on various types of images before any manipulation to reduce the file size like Quantization, Shift Coding or other methods.
The results of the conducted tests that applied on different types of images indicated that the difference between images in the YIQ and YUV color spaces is too small, so the difference between YIQ and YC_bC_r is taken into consideration in all comparisons. The tested results proved that the YC_bC_r color space is the best to use in images when they have sharpen edges or in highly detailed images and the difference in the PSNR is more than (1dB), this color space is also preferred in big images, while the effect of the three LC color spaces is not mentioned in the images with small sizes and less detailed images and any of these spaces can be used without affecting to quality of the image. The tests proved that the YIQ and YUV transform take less encoding time except in the detailed images.

Keywords : Haar Wavelets, LC Color Spaces, YIQ, YUV and YC_bC_r.

1. Introduction
Wavelets are functions which allow data analysis of signals or images, according to scales or resolutions. wavelets have found more and more applications in computer graphics, such as image compression, digital image processing, and feature detection [1].The processing of signals by wavelet algorithms in fact works much the same way the human eye does; or the way a digital camera processes visual scales of resolutions, and intermediate details. But the same principle also captures cell phone signals, and even digitized color images used in medicine. Wavelets are of real use in these areas, for example in approximating data with sharp discontinuities such as choppy signals, or pictures with lots of edges. It turns out that the low levels of the discrete wavelet transform contain the unimportant image features, so quantizing or discarding these coefficients can lead to lossy compression that is both efficient and of high quality.
Two of the greatest conundrums in digital image processing today are how to minimize the storage requirements for colored images, and how to retrieve a colors image from a grayscale image, that is, how to color a grayscale image. The compression is achieved as the color information is now stored in a grayscale image which inherently requires less storage space than its color equivalent. Minimization of storage requirements for colored images has been studied extensively and many compression algorithms exist, both lossy and lossless, that perform extremely well. In fact, many of these algorithms have been standardized and are actively used today, such as the JPEG algorithm [2].
This paper analyzes the using of Haar Wavelet transform on different color representations which applied on color images, the performance in quality and time using each space is considered.

2. LC Color Spaces
For digital still images, the Red-Green-Blue color space, known as RGB, is commonly used. In a RGB representation, 1 byte (8 bits) is used to represent the brightness of each of the three primary colors, which gives a range of [0,255]. It is well known that the RGB components of color images are highly correlated and if the wavelet transforms of each color component is obtained, the transformed components will also be highly correlated therefore the RGB model representation is a very redundant one [3]. The following terms are used to define color light:
1. *Brightness* or *Luminance*: This is the amount of light received by the eye regardless of color.
2. *Hue*: This is the predominant spectral color in the light.
3. *Saturation*: This indicates the spectral purity of the color in the light.
The LC representation is another common representation of color, which is based on “luminance” (L), and “chrominance” (C) values. Luminance reflects the brightness and by itself gives a grey scale version of the image. Luminance is more important for subjective good image quality than chrominance. The chrominance (color) components (i.e. Hue and Saturation) provide the additional information needed to convert a grey scale image to a color image [4].
The idea is to separate the brightness information of an image from its color. By separating brightness and color, it is possible to transmit a picture in a way that the color information is undetected by a black and white receiver, which can simply treat the brightness

as a monochrome signal [5]. In this paper the following color spaces are taken into consideration:

2.1. YIQ Color Space

YIQ and YUV are the 2 commonly used color models in video. YIQ is the color space used in North and Central America. "I" stands for "in phase" and "Q "stands for “quadrature,” referring to the components used in quadrature amplitude modulation [6]. The Y component gives luminance and the I and Q components give the chromaticity values of the color image. The following conversion matrixes are used to convert the RGB components to the YIQ and to get the RGB values from the YIQ components [2]:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.598 & -0.275 & -0.321 \\ 0.212 & -0.523 & 0.311 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad \ldots\ldots(1)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 0.956 & 0.621 \\ 1 & -0.271 & -0.647 \\ 1 & -1.107 & 1.407 \end{bmatrix} * \begin{bmatrix} Y \\ I \\ Q \end{bmatrix} \quad \ldots\ldots(2)$$

2.2. YUV Color Space

YUV is a color space that encodes a color image or video taking human perception into account, allowing reduced bandwidth for chrominance. Y is the luminance and U and V are chrominance values. The advantage of this color system is that the human perception for the Y component is substantially more sensitive than the U or V components. To get the RGB to YUV conversion and RGB values from the YUV components, the following conversion matrixes can be used [7]:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & 0.100001 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad \ldots\ldots(3)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 0.7495 & -0.509 & 1.1398 \\ 1.0836 & -0.2247 & -0.5806 \\ 0.9708 & -1.9729 & 0.000014 \end{bmatrix} * \begin{bmatrix} Y \\ U \\ V \end{bmatrix} \quad \ldots\ldots(4)$$

2.3. YC_bC_r Color Space

In YC_bC_r color space, Y is the single component that represents luminance. Cb and Cr store the color information where Cb stands for difference between the blue component and a reference value, and Cr is the difference between the red component and a reference value and it is used for the lossy compression [4]. The RGB to YC_bC_r components conversion and getting the RGB values from the YC_bC_r components matrixes is given below:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2989 & 0.5866 & 0.1145 \\ -0.1688 & -0.3312 & 0.5 \\ 0.5 & -0.4184 & 0.0816 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad \ldots\ldots(5)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & -0.001 & 1.402 \\ 1 & -0.3441 & -0.714 \\ 1 & -1.7718 & 0.001 \end{bmatrix} * \begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} \quad \ldots\ldots(6)$$

3. Haar Wavelet Transform

Wavelets provide a powerful set of tools for handling fundamental problems in science and engineering, such as signal compression, edge detection and fingerprint compression and image de-noising. The wavelet transform has emerged as a cutting edge technology, within the field of signal & image analysis. Wavelets are a mathematical tool for hierarchically decomposing functions. Though routed in approximation theory, signal processing, and physics, wavelets have also recently been applied to many problems in computer graphics including image editing and compression, automatic level-of-detailed controlled for editing and rendering curves and surfaces, surface reconstruction from contours and fast methods for solving simulation problems in 3D modeling, global illumination and animation [8].

An image is a two-dimensional array of pixel values. To illustrate how the Haar transform is used to compress an image, we start with a single row of pixel values, i.e., a one-dimensional array of *n* values. For simplicity we assume that *n* is a power of 2. If *n* has a different value, the data can be extended by appending zeros. After decompression, the extra zeros are removed.

The Haar wavelet transform computes the wavelet transform of the image by alternating between rows and columns. The first step is to calculate averages and differences for all the rows. This creates averages in the left half of the image and differences in the right half. The second step is to calculate averages and differences for all the columns, which results in averages in the top-left quadrant of the image and differences elsewhere. Steps 3 and 4 operate on the rows and columns of that quadrant, resulting in averages concentrated in the top-left subquadrant. Pairs of steps are repeatedly executed on smaller and smaller subsquares, until only one average is left, at the top-left corner of the image, and all other pixel values have been reduced to differences. They transform the original pixels into a few large numbers and many small numbers.

Figure (1b) shows the results of applying the Haar transform once to the rows of the image. The right half of this figure (the differences) is mostly zeros, reflecting the uniform nature of the image. However, traces of the vertical line can easily be seen (the notation 2 indicates a negative difference). Figure (1c) shows the results of applying the Haar transform once to the columns of Figure (1b).

The upper-right subband now features and the lower-left subband are denoted by HL and LH, respectively. The lower-right subband, denoted by HH, reflects diagonal image artifacts . Most interesting is the upper-left subband, denoted by LL, that consists entirely of averages. This subband is a one quarter version of the entire image, containing traces of both the vertical and the horizontal lines [9].

(a)

12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12
12	12	12	12	14	12	12	12

(b)

12	12	13	12	0	0	2	0
12	12	13	12	0	0	2	0
12	12	13	12	0	0	2	0
12	12	13	12	0	0	2	0
12	12	13	12	0	0	2	0
16	16	15	16	0	0	2	0
12	12	13	12	0	0	2	0
12	12	13	12	0	0	2	0

(c)

12	12	13	12	0	0	2	0
12	12	13	12	0	0	2	0
14	14	14	14	0	0	0	0
12	12	13	12	0	0	2	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
4	4	2	4	0	0	4	0
0	0	0	0	0	0	0	0

Figure 1: An 8×8 Image and Its Sub bands Decomposition

4. Usage of Haar Wavelet on LC Color Spaces

The following algorithm steps are followed on each color image in the (appendix A):

1. Start
2. Input: The original image in RGB color space.
3. Convert the RGB color space into one of the LC color spaces using the appropriate conversion matrix using equations (1, 3, and 5), various color spaces are used hence the procedure is outlined for a general color space "ABC" , "A" stands for L component, "B" and "C" stands for chrominance components.
4. Apply Haar Wavelet transform on each LC component "ABC" (see Fig.2), the transform will divide each component it into 4 regions (LL, LH, HL and HH).

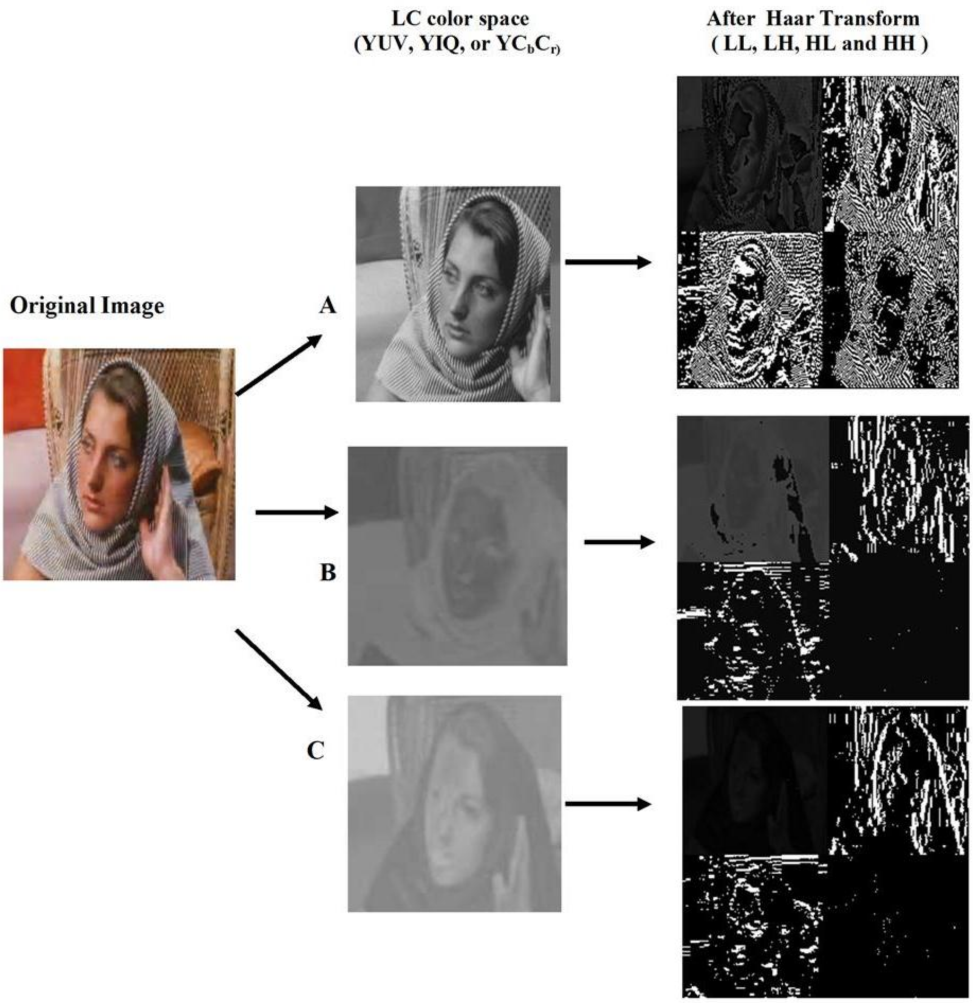

Figure 2: The Image transforms steps

5. The "A" component is left untouched because it is the most sensitive part of the image and contains 80% of the image details.
6. In "B" and "C" components, the LH, HL and HH regions is ignored or replaced by scaled down versions of the image in compression algorithms because it is contains little information.
7. The inverse Haar transform is now applied to each of the grayscale images (A,B and C) in the spatial domain. The approximations for the "ABC" components are used to convert the image back to the RGB color space using the appropriate conversion matrices in equations (2, 4, and 6) for the YIQ, YUV and YC_bC_r components respectively.
8. Record the PSNR and encoding time of the reconstructed images into table (1) for the YIQ, YUV and YC_bC_r components respectively.
9. Compare and record the difference in the PSNR and time of the three color spaces for the image.
10. End

The algorithm is applied on 14 different types and sizes of images shown in (Appendix A) using the three color space conversions to find the differences in PSNR, and encoding time to decide what is the suitable color space is best to be used with minimum loss in quality and time before any manipulation on the image.

5. Experimental Results and Analysis

The performance of the proposed system was evaluated using quality metrics like compression time, and Peak Signal to Noise Ratio (PSNR). The Peak Signal to Noise Ratio (PSNR) is calculated using the following formula[6]:

$$PSNR = 10\log_{10}\left(\frac{\Delta_u^2}{MSE(u,u')}\right) \quad \ldots\ldots\ldots(7)$$

Where,

Δ^2 is the difference between maximum and minimum pixel values of image u.

$u = (u_0, u_1,\ldots, u_{n-1})^T$ and $u' = (u'_0, u'_1,\ldots, u'_{n-1})^T$ are n-vector representations of the original and reconstructed images, respectively. The Mean Square Error(MSE) is calculated using the following formula[6]:

$$MSE(u,u') = \frac{1}{n}\sum_{j=1}^{n-1}(u_j - u'_j)^2 \quad \ldots\ldots\ldots\ldots(8)$$

Table (1) and figure(3) lists the PSNR parameters of the 16 images after transforming them to the three color spaces (YIQ, YUV, and YC_bC_r) and applying Haar wavelet transform. The YUV and YIQ have nearly the same quality, so the differences between the YIQ and YC_bC_r color space are taken in all comparisons. According to the differences PSNR shown in Table (1) and figure(4), the images in (Appendix A) are classified into as the following types:

1-The size of the image is very important to decide the best color space to use. In large images, the best color space is the YC_bC_r color space as in Bear and House image, while in the Fingp any color space can be used.

2-In Images that have the same size, also the PSNR differs depending on the type of the image. In smooth images like Lena and Pepper the YUV gives good Quality, but in the detailed images as Baboon and Bird, and images with sharpen edges as Car, Map, the YC_bC_r is also best to use.

3-Medical images are highly detailed images, the difference between the three color spaces is high, and because these types of images contain sensitive information must use the proper color space, and it is also YC_bC_r color space.

4-The algorithm basically provides a small Compression Ratio (CR =0.67) because of using Haar Transform and CR=1.35 (I.e. =36% from the image size) when ignoring The LH, HL and HH regions "B" and "C" components in saving operation. After that the researcher can use any encoding method he wants to raise the CR like Quantization, run length encoding, and so on.

5-In most of test results the YUV and YIQ proved best encoding time than $YC_bC_{r,}$ (Figure 5) even if the difference is not mentioned (about 0.2 to 0.5 sec), but in many researches which concentrated on the time parameter like the fractal encoding which is slower than Haar Wavelet, the YUV and YIQ take less encoding time except in baboon which is a detailed image.

In general, the YC_bC_r color space gives higher quality in most cases to transform images before applying Haar Wavelet, while YUV and YIQ color spaces are preferred in most of the images if the encoding time is importnt.

Table (1) the PSNR on the tested images

Image	Size (Pixels)	YUV PSNR(dB)	YIQ PSNR(dB)	YC_bC_r PSNR(dB)	Difference
FingPr	166x189	62.1	62.1	62.1	0
Lena	256x256	49.49	49.26	49.85	0.59
Peper	256x256	49.7	49.47	50.4	0.93
Birds	256x256	50.96	50.61	51.65	1.04
Car	256x256	51.53	51.06	52.22	1.16
Baboon	256x256	50.49	49.92	51.85	1.93
Barbra	256x256	51.3	50.98	53.39	2.41
Flower	384x312	50.35	49.94	50.99	1.05
Map	401x407	50.5	49.7	52.5	2.8
Med1	400x300	51.99	51.13	53.4	2.27
Med2	301x295	52.3	50.6	53.5	2.9
Med3	400x255	53.54	52.06	55.25	3.19
House	500x318	51.95	50.77	53.94	3.17
Bear	500x500	50.7	50.18	52.11	1.93

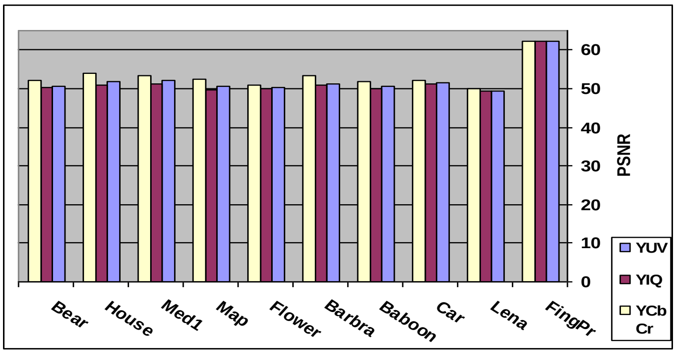

Figure 3: The PSNR for the some of tested images Using the three LC color spaces

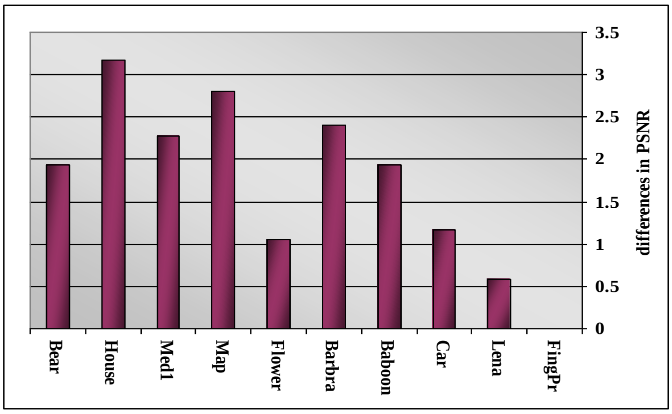

Figure 4: The difference in PSNR between the YUV & YCbCr color spaces for the tested images

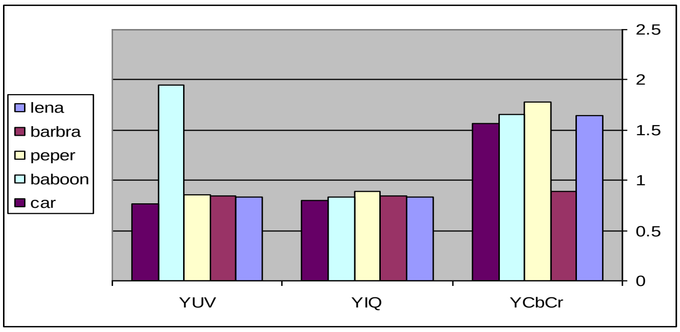

Figure 5: The difference in encoding time among the three color spaces

6. Conclusions

This work analyzes the bitmap images using Haar wavelet with various color spaces for many different categories of colored images. It can be concluded that when the images are small or contains little details and no edges (i.e. smooth images), all color spaces (YUV, YIQ, and YCbCr) are suitable and gives a little difference in quality, and the first two color spaces (YIQ and YUV) gives nearly the same PSNR when applied to the image, but when the image contains edges or more details then the YCbCr is more suitable to use because it gives higher quality especially with big size images, the difference in quality always was between 0.1 and 3.5 at most. This work helps to decide the best quality obtained when using haar wavelet in compression on the colored images, and it is better to convert the image to grayscale color spaces instead of the RGB color space in Haar compression before doing any other analysis. To get a good compression ratio, analysis like Quantization and entropy encoding can be applied, like run length encoding, Differential Pulse Code Modulation (DPCM) or shift encoding.

Appendix A

((List of Images Used to Determine the Effect of Using Different Color Spaces On Haar Wavelet Transformed Images))

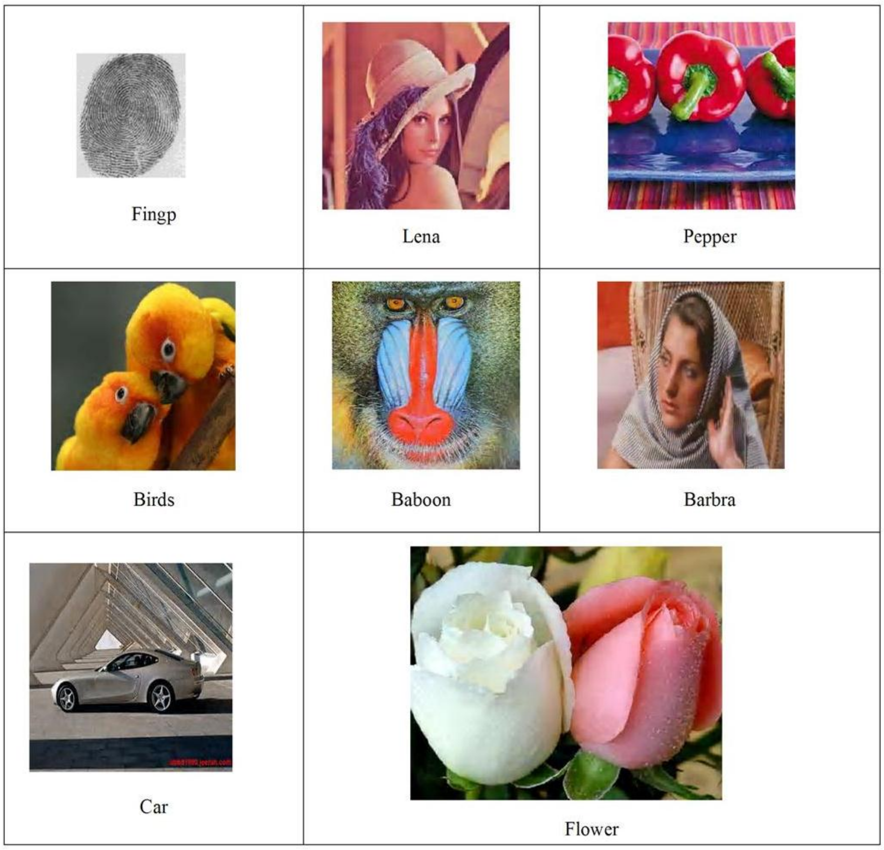

Figure A1: The tested images (to be continue)

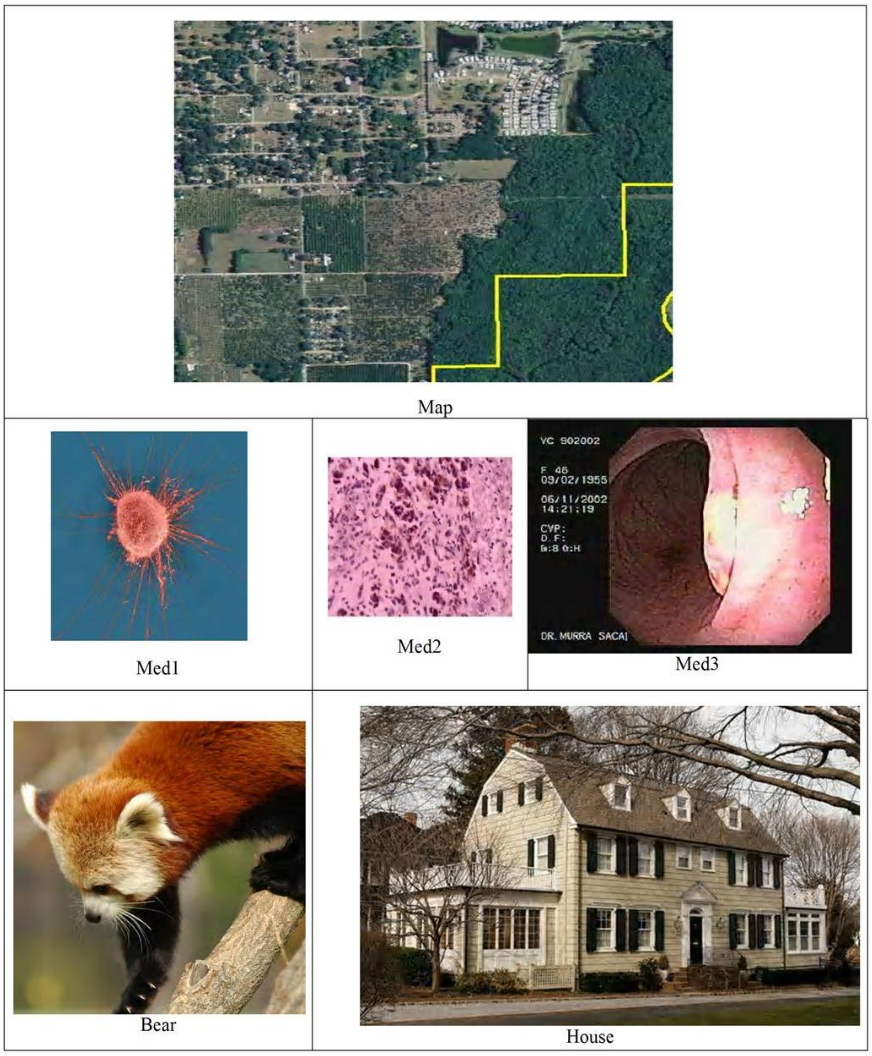

Figure A2: The tested images (continued)

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تأثير استخدام فضاءات الالوان المختلفة على الصور المعالجة بالتحويل الموجي الصلب

نفارت الياس يوسف

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الملخص

التحويلات المويجية (Wavelets Transform) هي مجموعة من الطرق الكفوءة المستخدمة لمعالجة مشاكلِ أساسية في العلوم والهندسة، مثل كبس الصور، تمييز الحافات، وكبس ملفات البصمة وازالة التشويش للملفات السمعية. يقوم هذا البحث بتطبيق التحويل المويجي (Haar Wavelet) على انواع مختلفة من الصور وباحجام مختلفة بعد تحويل الصور الملونة نوع (RGB) الى صور رمادية اللون (grayscale) (اي فضاء الالوان LC الذي يستند على قيم السطوع Luminance والنقاوة Chrominance) كفضاءات الالوان نوع YIQ، YUV و YC_bC_r وذلك لمعرفة مدى تأثير هذا النوع من التحويلات على كفاءة الصورة (quality) المعتمدة على قياس ال PSNR.ان هذا النوع من التحويل يؤدي الى خسارة قليلة في كفاءة الصور، وهذا البحث يساعد الباحثين لاختيار فضاءِ اللونِ الافضل لاستخدامه في كبس الصور باستخدام التحويل المويجي Haar wavelet لمختلف انواع الصور وقبل اجراء اي معالجة لتقليل حجم الملف كالتقريب (Quantization) او التشفير بالتزحيف (Shift Coding) او طرق اخرى.

اثبتت نتائج الفحوصات التي طبقت على مختلف انواع الصور بان الفرق في الصور بعد تحويلها الى فضاء اللون YIQ وبين فضاء اللون YUV قليل جدا، لذا فقد اعتمد الفرق بين فضائي اللون YIQو YC_bC_r في جميع المقارنات لايجاد الطريقة الافضل. اثبتت النتائج بانه يفضل استخدام فضاء اللون YC_bC_r عندما يراد كبس صور تحوي حافات حادة او تفاصيل دقيقة، حيث ان الفرق في الكفاءة يكون اكثر من (1 dB) وكذلك يفضل هذا النوع من التحويل في الصور ذات الاحجام الكبيرة، بينما كان تأثير انواع الفضاءات اللونية الثلاثة متقارب في الصور ذات الحجم الصغير ونفس الشيء ينطبق على الصور ذات التفاصيل القليلة ويمكن استخدام اي منها بدون ان يؤثر ذلك على كفاءة الصورة. اثبتت نتائج الاختبارات ان فضاءات الالوان نوع YIQ و YUV تحتاج الى وقت اقل لتحويل الصور عدا في الصور ذات التفاصيل الكثيرة.

الكلمات المفتاحية: Wavelets, LC Color Spaces, YIQ, YUV and YC_bC_r.