Study Chromatic Spaces YUV, HSI and Comparison in Analysis of Images Dust

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***Abstract*—In this paper, were compared to YUV, HSI color space, adopted in analyze the dust images. we designed the system captured images which graded for high to very low dusty by using HeNe laser, in these images we calculated the normalize mean square error (NMSE) for each components in YUV, HSI and RGB color space separately, and the basic components in the structure similarity Index (SSIM) are (contrast, structure and luminance) moreover the mean for all has been calculated. We noted from results spaces YUV, HSI chromatic that there is a similarity in analysis of images dusty when compared. This means that the use of any color space gives almost the same results.**

Keywords—The dust images, Image quality, contrast, luminance, YUV, HSI and RGB color spaces.

1. Introduction

Image quality is a characteristic of an image that measures the Image degradation. In many cases the image of outdoor scenes are degrade by the improper weather Condition. We have also know that light reflected from a surface is scatted in the atmosphere before it reaches the camera is Due to the presence of aerosol such as dust must and fames[1].Dust weather can significantly influence the quality of images since capturing often leads to undesirable degradation such as poor contrast, deficient colors or color cast[2]. According to the visibility of dust weather there are floating, dust blowing, sandstorms and strong sandstorms. Dust will affect scattering and absorption of light, hence it will cause severe degradation of video images [3].dusty image analysis it is important case in the dehazing image and image quality assessment, the problems which affect in quality analysis of image can be divided into two major categories: dynamic and static. Dynamic problem is such problem which appearing when objects fast-move such as motion tremors and motion blur; static problem is that always occur in a video sequence, and have no relation with object movement, such as various of noise, edge blur, poor contrast[3,4]. In this paper, the dusty color images have been analyzed depending on two objectives quality are the SSIM and NMSR. The each component of Chromaticity spaces YUV, HSI are employed in SSIM and NMSR and we compared between them for each space, the important of this procedure is determine the quality of dusty image and the style of it enhanced. In this search we attempt to answer the question what is the space more effective in dusty image analysis. Moreover the components of SSIM in the lightness (Luminance, structure and contrast) it has studied.

2. YUV color space

The color television systems PAL and SECAM, developed in Germany and France, use the YUV color space for transmission. The Y component is identical with the one of the YIQ color space. The values in the R_M G_M B_M color space can be transformed with

$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ -0.418 & -0.289 & 0.437 \\ 0.615 & -0.515 & -0.100 \end{pmatrix} \begin{pmatrix} R_M \\ G_M \\ B_M \end{pmatrix}. (1)$$

in to the values in the YUV color space [5]. On account of the low information content, the U and V signals, which are usually related to the Y signal, are reduced by half (two successive image pixels each having a separate Y portion, but with a common color type) and by a quarter for simple demands. The I and Q signals of the YIQ color space are determined from the U and V signals of the YUV color space by a simple rotation in the color coordinate system. The following applies [5]:

$$I = - U.\sin(33) + V.\cos(33),$$

$$Q = U.\cos(33) + V.\sin(33) \ldots.(2)$$

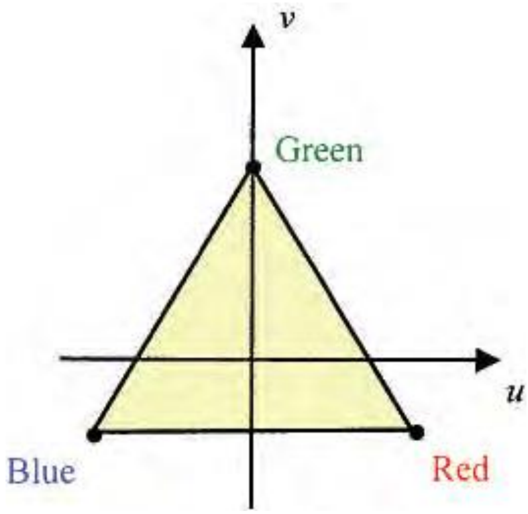
Presentations in the YIQ and YUV color space are very suitable for image compression since luminance and chrominance can be coded with different numbers of bits, which is not possible when using RGB values.In the literature, YUV also indicates a color space, in which U corresponds to the color difference red-blue and V to the color difference green-magenta. Y corresponds to the equally weighted (arithmetical) averages of red, green, and blue. We will denote this color space with YUV for a better distinction. A linear correlation exists between the YUV color space and the RGB system which is given by the transformation

$$(Y\ U\ V) = (R\ G\ B)\begin{pmatrix} \frac{1}{3} & \frac{1}{2} & \frac{-1}{2\sqrt{3}} \\ \frac{1}{3} & 0 & \frac{1}{\sqrt{3}} \\ \frac{1}{3} & \frac{-1}{2} & \frac{-1}{2\sqrt{3}} \end{pmatrix} \ldots.(3)$$

Brightness normalization can be defined by:

$$u = \frac{U}{R+G+B}\, and\ v = \frac{V}{R+G+B} \ldots.(4)$$

If u and v form the axes of a Cartesian coordinate system, then red, green, and blue stretch an equilateral triangle in which black lies in the origin as in Figure(1)



Figure(1) The uv plane of the YUV color space

3. HSI color space

In the HSI color space hue, saturation, and intensity are used as coordinate axes. Figure (2) shows a possible representation of the HSI color space. This color space is well suited for the processing of color images and for visually defining interpretable local characteristics. a color q = (R , G, B) is given in the RGB color space. The hue h of the color q characterizes the dominant color contained in q. Red is specified as a reference color. Because of that, h = 0 and h = 360 correspond to the color red. h i s given by:

$$h = \begin{cases} \partial & if\ B \le G \\ 360 - \partial & if\ B > G \end{cases} \ldots.(5)$$

With

$$\partial = arccos\left(\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2 + (R-B).(G-B)}}\right) \ldots.(6)$$

The saturation s of the color q is a measurement of color purity. This parameter is dependent on the number of wavelengths that contribute to the color perception. The wider range of the wave lengths the lower the purity of the color. The more narrow the range of the wave lengths, the higher the purity of the color. The extreme case s = 1 is true for a pure color and the extreme case s = 0 for an achromatic color. s is given by:

$$s = 1 - 3.\frac{\min(R, G, B)}{R+G+B} \ldots.(7)$$

The intensity I of the color q corresponds to the relative brightness in the sense of a gray-level image. The extreme case I = 0 corresponds to the color black. The intensity is defined in accordance with

$$I = \frac{R+G+B}{3} \ldots.(8)$$

For the color q = (R, G, B) in the RGB color space, a representation (H, S ,I) of this color is given in the HSI color space [6,7].

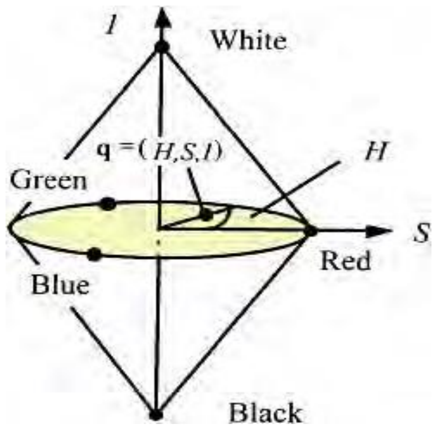


Figure (2) The HSI color space

4- Image Quality Assessment by Distortion Model

Images may be corrupted by degradation such as linear frequency distortion, noise, dust and blocking artifacts. These sources of degradation may arise during image capture or processing, and have a direct bearing on visual quality [8]. In image processing, the model widely used to describe the formation of a haze image is given by [9,10]:

$$I(x) = J(x)t(x) + A\big(1 - t(x)\big) \dots (9)$$

A is the global atmospheric light, and t is medium transmission $J(x)$ is the original surface radiance vector at the intersection point of the scene with the real-world ray. $J(x)t(x)$ is direct attenuation term [10], representing the scene radiation decay effect in the medium , $A\big(1 - t(x)\big)$ is air light term [10], describing the light scattering from atmosphere particles inducing color distortion. The SSIM metric is based on the evaluation of three different measures, the luminance, contrast, and structure comparison measures are computed as [11]:

$$l(x,y) = \frac{2\mu_X(x,y)\mu_Y(x,y) + C_1}{\mu_X^2(x,y) + \mu_Y^2(x,y) + C_1} \dots\dots (10)$$

$$c(x,y) = \frac{2\sigma_X(x,y)\sigma_Y(x,y) + C_2}{\sigma_X^2(x,y) + \sigma_Y^2(x,y) + C_2} \dots\dots (11)$$

$$s(x,y) = \frac{\sigma_{XY}(x,y) + C_3}{\sigma_X(x,y)\sigma_Y(x,y) + C_3} \dots\dots (12)$$

Where X and Y correspond to two different images that we would like to match, i.e. two different blocks in two separate images, μ_x, σ_x^2, and σ_{xy} the mean of X, the variance of X, and the covariance of X and Y respectively where[11]:

$$\mu(x,y) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q)X(x+p,y+q) \dots (13)$$

$$\sigma^2(x,y) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q)[X(x+p,y+q) - \mu_X(x,y)]^2 \dots (14)$$

$$\sigma_{XY}(x,y) = \sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q)[X(x+p,y+q) - \mu_X(x,y)] \dots (15)$$

$$[Y(x+p,y+q) - \mu_Y(x,y)] \dots (16)$$

Where $w(p,q)$ is a Gaussian weighing function such that:

$$\sum_{p=-P}^{P} \sum_{q=-Q}^{Q} w(p,q) = 1 \dots (17)$$

And C_1, C_2, and C_3 are constants given by $C_1 = (K_1 L)^2$, $C_2 = (K_2 L)^2$, and $C_3 = C_2/2$. L is the dynamic range for the sample data, i.e. $L = 255$ for 8 bit content and $K_1 << 1$ and $K_2 << 1$ are two scalar constants. Given the above measures the structural similarity can be computed as [11]:

$$SSIM(x,y) = [l(x,y)] \cdot [c(x,y)] \cdot [s(x,y)] \dots (18)$$

5. Experiment Results

A system has been designed to measure the amount of the particle of dust that is distorted the image, which is made up of firm glass box, Fan, laser HeNe, Camera stand, camera and Lux meter as in Figure (3). The Fan is used to stirs the dust that is putting in the box in the same time the lux meter measured the laser intensity. When a specific amount of the dust is added in the box the fun will be stir the dust, after small time the dust is gets still at the bottom of the box. The images are taken from this time during the dust is stirs to it gets on the bottom, we can consider all images are the dust image but the last image is approximately optimal images.in this system if the dust is increased the laser intensity is decreased. Figures (4) and (5) the images used in the study which shows the amount of dust from the high to low. In the figures (6a,8a,10a,12a) illustrated the relationships between the max.illuminance and the SSIM for the value component in YUV, HSI color spaces for data images, from these figures we can see the max.illuminance increasing with increased the SSIM due to decrease the dust. And the relationships between the max.illuminance and SSIM components was illustrate in the figures (6b ,8b,10b,12b) to spaces chromatic (YUV,HSI), we noted the contrast component is approximately remaining constant whereas the behaviors of structure and luminance are similar the value component, but the SSIM is high in the contrast. The figures (7ab,9ab,11ab,13ab) are illustrated the relationship between the max.illuminance and the NMSE for RGB and each component in YUV, HSI for data images, we saw the NMSE is decreasing with increased the max.illuminance in the all component, and the chromatic components U ,V, hue and saturation are more effected by the dust due to the error is high, because increasing the white light in these images.

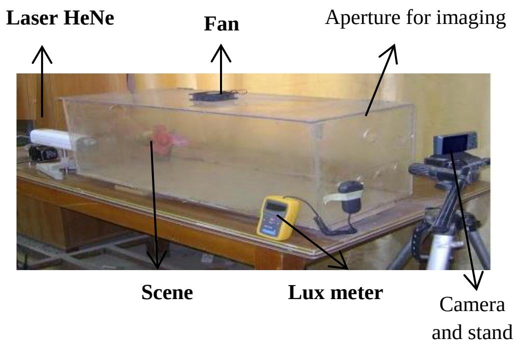


Figure (3) represents the system used to measure the amount of dust on the scene

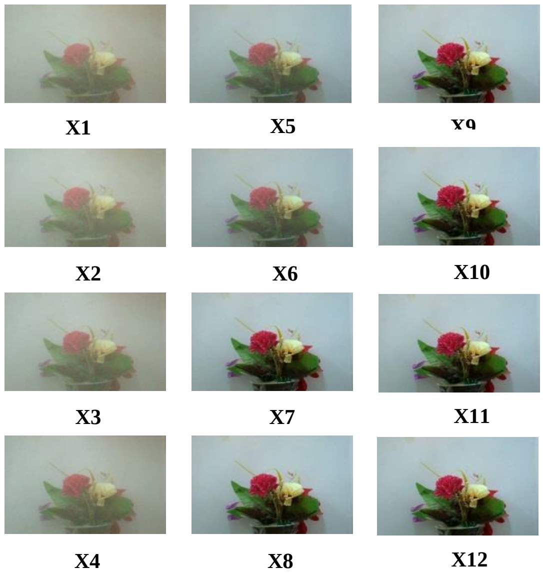


Figure (4) First group of the dust images with different dust levels from maximum in x1 to very low in x12

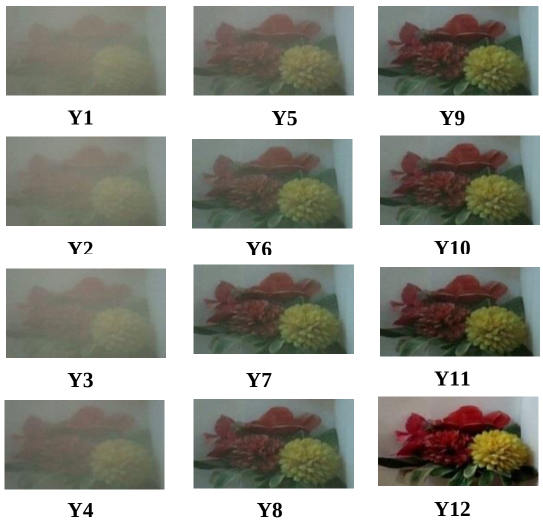


Figure (5) Second group of the dust images with different dust levels from maximum in y1 to very low in y12

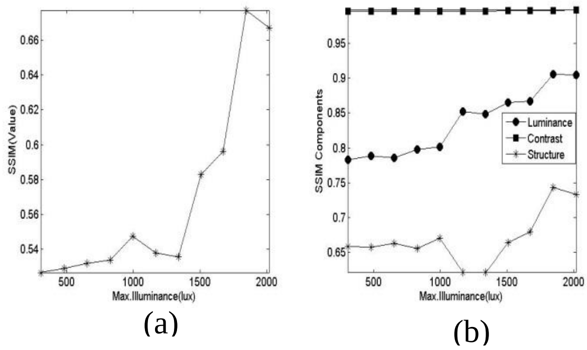


Figure (6) The max.illuminance as a function of SSIM for the value component in YUV color space (in a) and (in b) the components of SSIM are (luminance, contrast and structure) for first group images

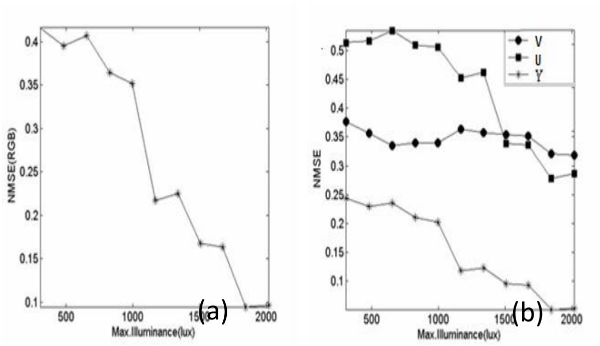


Figure (7) Relationship between Max.illuminance and NMSE (a) for RGB component and (b) for Y,U and V value components for first group images.

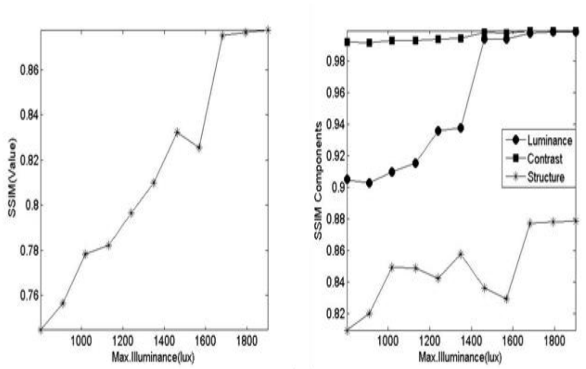


Figure (8) The Max.illuminance as a function of SSIM for the value component in YUV color space (in a) and (in b) the components of SSIM are (luminance, contrast and structure) for second group images.

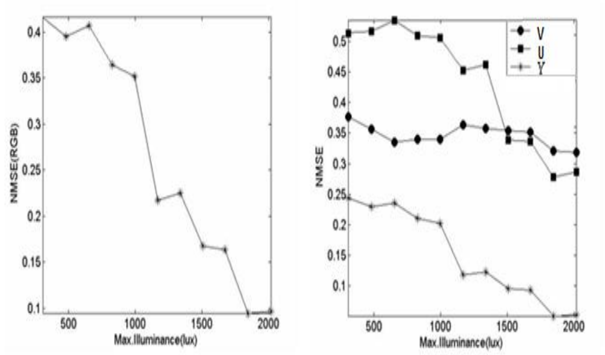


Figure (9) Relationship between Max.illuminance and NMSE (a) for RGB component and (b) for Y,U and V, value components, for second group images.

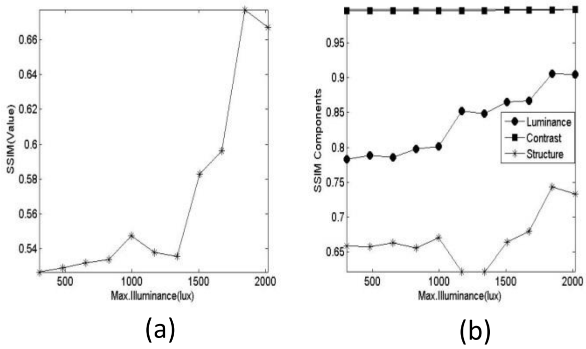


Figure (10) The Max. illuminance as a function of SSIM for the Value component in HSI color space (in a) and (in b) the components of SSIM are (Luminance, Contrast and Structure),for first group images

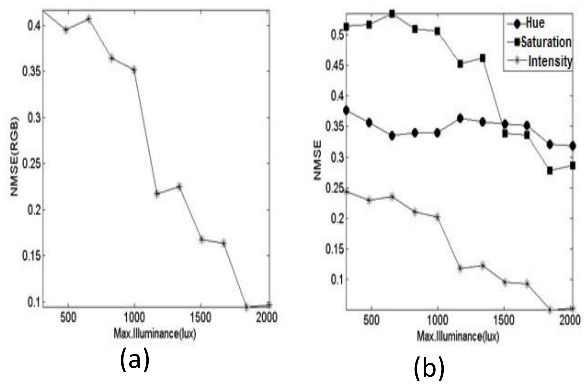


Figure (11) Relationship between Max. illuminance and NMSE (a) for RGB component and (b) for Hue ,saturation and intensity value components, for first group images.

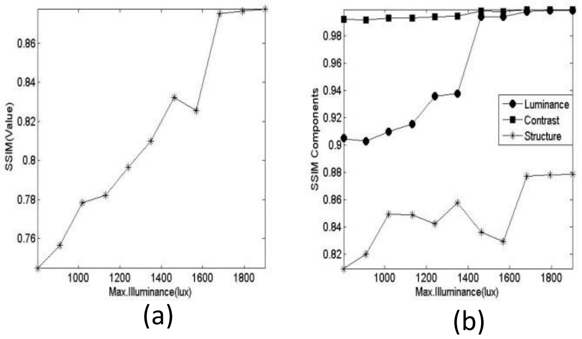


Figure (12) The Max. illuminance as a function of SSIM for the Value component in HIS color space (in a) and (in b) the components of SSIM are (Luminance, Contrast and Structure), for second group images.

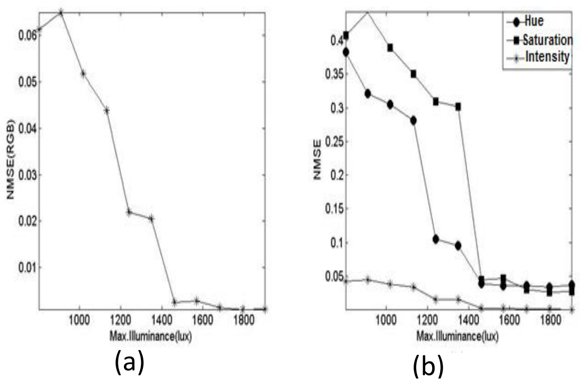


Figure (13) Relationship between Max.illuminance and NMSE (a) for RGB component and (b) for Hue,saturation and intensity value components, for second group images.

Conclusion

In this paper, were compared to YUV, HSI color spaces adopted in study and analyze the dust images, and it gave almost the same results in the analysis of images of dust, since the metric SSIM for value the structure follows the contrast is decreasing due to the dust compare with the luminance in both color spaces. It means that the use of any color space gives almost the same results in analyze the dust images.

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