NO REFERENCE IMAGE QUALITY ASSESSMENT DEPENDING ON YCbCr AND L*u*v*

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Abstract

Image quality assessment is a complicated and hard process, because of its independent on reference image, this process is done by some no reference metrics. In this paper the quality of images were assessed by a no reference metric, this metric is (The entropy of first derivative (EFD)), also Gaussian blurring were assumed as a distortion, and to estimate the efficiency of the no reference metric in assess the quality of colored images it is necessary to compare the results with the results of some reference metrics, we depended on (Normalize mean square error (NMSE) and structural similarity index measurement (SSIM)) as a reference metrics.Furthermore, two color spaces were applied (YCbCr and L*u*v*) to find the best color space to working on. In the first step of the work the selected images were distorted by Gaussian blurring then the quality of the distorted images were measured by the reference metrics, this is done in the two color spaced were used, after that the no reference metric were applied to assess the quality of the distorted images, finally, the results were compared with the results of the reference metrics by plotting and by finding the correlation coefficients between the carves of reference and no reference metrics to find the best color space to working on.

Keywords: No reference image, EFD, quality assessment, YCbCr and L*u*v*

1.Introduction:

Objective image quality measures have been developed to quantitatively predict perceived image quality. They are of fundamental importance in numerous applications, such as to benchmark and optimize different image processing systems and algorithms, to monitor and adjust image quality, and to develop perceptual image compression and restoration technologies, etc. As an important approach for objective image quality assessment, noreference image quality assessment seeks to predict perceived visual quality solely from a distorted image and does not require any knowledge of a reference (distortion-free) image. Noreference image quality measures are desirable in applications where a reference image is expensive to obtain or simply not available. The intrinsic complexity and limited knowledge of the human visual perception pose major difficulties in the development of no-reference image quality measures. The field of noreference image quality assessment remains largely unexplored and is still far from being a mature research area. Despite its substantial challenges, the development of noreference image quality measures is a rapidly evolving research direction and allows much room for creative thinking [1].In2007,F. Crete etal,suggested a no reference quality toestimate the blur distortion by computing the intensity variations between neighboring pixels of theinput image[2], also in 2008, Xin Wangetal, presents a noreference blur metric for images and video using information contained in the image itself,they look at the sharpness of the sharpest edges in the blurred image, which contains information about the blurring [3], furthermore R. Ferzlietal, In 2009, presents a perceptual-based noreference objective image sharpness/blurriness metric by integrating the concept of just noticeable blur into a probability summation model[4]**,** but H. G. Al-Khuzaiin

2011, suggested a no reference quality tomeasure the quality of the color image based on changing in lightness and contrast[5], as well,A. Chetouanietal, in2012,proposed a no reference image quality assessment according to the degradation type by detecting and identifying the type of the degradation contained in the image before quantifying its quality[6]. In this paper a no reference metric were applied to assess the quality of blurred color images, considering two color spaces (YCbCr and L*u*v*).

2.Image quality measurement (IQM):

Measuring the quality of image is a complicated and hard process since humans opinion is affected by physical and psychological parameters. Many techniques are proposed for measuring the quality of the image but none of it is considered to be perfect for measuring the quality. Image quality assessment plays an important role in the field of image processing [7]. Image quality metrics are dividedin to two kinds subjective and objective,human visual system (HVS) is an example of subjective IQM.Most IQM are related to the difference between two images (the original and distorted image) and this type is called reference IQM, other IQM are not related to the difference between the two images like reduce reference IQM and no reference IQM.

3.No reference image quality metrics:

No reference image quality refers to the problem of predicting the visual quality of image without any reference to an original optimal quality image. This assessment is the most difficult problem in the field of image objective analysis [8], since many unquantifiable factors play a role in human perceptions of quality, such as aesthetics, cognitive relevance, learning, context...etc. [9]. No reference image quality is useful to many still image applications as assessment equality of high-resolution image, JPGE image compressed [10] moreover, this objective method can measure image equality depending on verity of lightness and contrast.

4.Mean and Normalize Squared Error (MSE), (NMSE)

The simplest and most widely used fidelity measure is the mean squared error (MSE) and the corresponding distortion metric, is given by [11]:

$$MSE = \sum_{x=1}^{M}\sum_{y=1}^{N}(I_n(x,y) - I(x,y))^2 \dots\dots\dots\dots (1)$$

And the Normalization Mean Squared Error (NMSE) is defined as [11]:

$$NMSE = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\left(I_n(x,y) - I(x,y)\right)^2}{\sum_{x=1}^{M}\sum_{y=1}^{N} I^2(x,y)} \dots\dots\dots\dots (2)$$

5.Structural Similarity Index Measurement(SSIM):

Wang etal[12],proposed structural similarity index as an improvement for universal image quality indexUIQI, the mean structural similarity index is computed as follows: Firstly, the original and distorted images are divided into blocks of size (8 * 8) and then the blocks are converted into vectors. Secondly, two means and two standard derivations and one covariance value are computed from the images as in (3), (4) and (5) [12].

$$\mu_x = \frac{1}{T}\sum_{i=1}^{T} x_i \, \mu_y = \frac{1}{T}\sum_{i=1}^{T} y_i \dots\dots\dots\dots (3)$$

$$\sigma_x^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})^2 \qquad \sigma_y^2 = \frac{1}{T-1}\sum_{i=1}^{T}(y_i - \bar{y})^2 \dots\dots\dots\dots (4)$$

$$\sigma_{xy}^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})(y_i - \bar{y}) \dots\dots\dots\dots (5)$$

wherex_i and y_i correspond to two different images, i.e. two different blocks in two separate images,μ_x, μ_y, $\sigma_x^2, \sigma_y^2$and $\sigma_{xy}^2$are the mean ofx_i, the mean of y_i, the variance of x_i, the variance of y_i, and the covariance of x_i and y_i respectively

Thirdly, luminance, contrast, and structure comparisons based on statistical values are computed like in UIQI, the structural similarity index measure between images x and y is given by (2.8) [11].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{({\mu_x}^2 + {\mu_y}^2 + c_1)({\sigma_x}^2 + {\sigma_y}^2 + c_2)} \dots\dots\dots\dots (6)$$

Where c_1 and c_2 are constants. SSIM is more accurate and consistence than MSE despite its cost more.

6.YCbCr color space:

The YCbCr color spaceis usedwidely in digital video. In this format, luminance information is represented by a single component, Y, and color information is stored as two color difference components Cb and Cr. Component Cb is the difference between the blue component and a reference value, and component Cr is the difference between the red component and a reference value [13]. The transformation used by IPT to convert from RGB to YCbCr is [14]:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.214 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \dots\dots\dots\dots (7)$$

7.CIE L*u*v* color space

This color space is based on the CIE Yu'v' color space and is a further attempt to linearize the perceptibility of unit vector color differences. It is a non-linear color space, but the conversions are reversible. Coloring information is centered on the color of the white point of the system, subscript n, (D65 in most TV systems). The non-linear relationship for Y* is intended to mimic the logarithmic response of the eye [15].

$$L^* = \begin{cases} 116\left(\frac{Y}{Y_n}\right)^{13} - 16 & if\ \frac{Y}{Y_n} > 0.008856 \\ 903.3\left(\frac{Y}{Y_n}\right) & if\ \frac{Y}{Y_n} \leq 0.008856 \end{cases} \dots\dots\dots\dots (8)$$

$$u^* = 13(L^*)(\acute{u} - \acute{u_n}) \dots\dots\dots\dots (9)$$

$$v^* = 13(L^*)(\acute{v} - \acute{v_n}) \dots\dots\dots\dots (10)$$

L^*scales from 0 to 100 for relative luminance ($\frac{Y}{Y_n}$) scaling from 0 to 1.

8.Gaussian blurring

The Gaussian blur is a type of image-blurring filter that uses a Gaussian function for calculating the transformation to apply to each pixel in the image [16,17]. The equation of a Gaussian function in two dimensions of the position x,y is given by:

$$G(x,y) = \frac{1}{\sqrt{2\pi s^2}} e^{-\frac{x^2+y^2}{2s^2}} \dots\dots\dots\dots (11)$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and s is the standard deviation of the Gaussian distribution (sigma). When applied in two dimensions, this formula produces a surface whose contours are concentric circles with a Gaussian distribution from the center point.

Values from this distribution are used to build a convolution matrix that is applied to the original image. The blurring image is given by [14].

$$Ib = I * G \ldots\ldots\ldots\ldots (12)$$

Where I is the original image, G is Gaussian function and Ib is the resulted blur image.

If we applied equation (11) in frequency domain, this can be done by using Fourier transform that given by [14]:

$$F(u,v) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} I(x,y)e^{-i2\pi(\frac{ux}{M}+\frac{vy}{N})} \ldots\ldots\ldots\ldots (13)$$

Where u is the frequency in x direction,$u=0,1,\ldots,M-1$ and v is the frequency in y direction,$v=0,1,\ldots,N-1$.

If I is the image to be blurred,Ib is the resulted blur image, and it is assumed that the blur function G in the same size, this can be done by:

1. Transform image in frequency domain by using Fourier transform F.
2. Multiply the transform image by the Gaussian blurs function.
3. Applied inverse furrier transform of the blurred image in step 2.

9.The Entropy of the First Derivative (EFD) of image

This method depending on the first derivative of an image,as in the following formula [18]:

$$I_d(x,y) = \frac{\partial^2 I(x,y)}{\partial x \partial y} \ldots\ldots\ldots\ldots (14)$$

Figure (3.2) shows the first derivative of high lightness and low lightness images. The entropy of the first derivative defined as follows [18]:

$$H(x) = \sum_{k}^{n} P(x_k)\log_2(\frac{1}{P(x_k)}) \ldots\ldots\ldots\ldots (15)$$

Where χ is a discrete random variable with possible outcomesx_1, x_2,...x_n,$P(x_k)$is the probability of the outcomex_k. The outcome is understood as a gray level in the lightness image and its probability is calculated by [18]:

$$P(x_k) = \frac{n_k}{N_t} \ldots\ldots\ldots\ldots (16)$$

Where $k = 1\,,2\,,\ldots n, n$ is the total number of possible lightness in the image, N_t is the total number of pixels, and n_k is the number of pixels that have lightness level x_k. The higher entropy value denotes a better contrast in image.

10.The results and discussion:

In this section, we study the reference and no reference metrics were appliedto measure the quality of colored images distorted by Gaussian blurring. Firstly, we apply the two reference metrics (NMSE and SSIM) in the two color spaces were used (YCbCr and L*u*v*) to measure the quality for 6 color images, the results was as in figures bellow, in figures (2) and (3) we see the results of the NMSE as a function of sigma (blurring factor), were in figures (4) and (5) we see the results of the SSIMas a function of sigma. Secondly, we apply the no reference metric EFD to assess the quality and comparing the results with the results of thereference metrics as in figures (6) and (7), were in tables (1) and (2) we see the amounts of correlation coefficients between the (EFD and NMSE) and (EFD and SSIM) respectively.

Figure (1): Images used in the study

11.Conclusions

Form these figures and tables we can note:

1. We find that In YCbCr and L*u*v* color spaces, blurring affect the achromatic components (Y and L) more than chromatic components (CbCr and uv).
2. The amounts of NMSE and SSIM areincreasingwith the decreasing of sigma, in other word, NMSE and SSIM are increasing with the decreasing of blur, because sigma has an inversely relationship with blur.
3. In the EFD metric the quality decreasing directly with the decreasing of sigma, this means that, this metric has been succeeded to measure the quality.
4. From the amounts of the correlation coefficients we found that YCbCr color space is better to assess the quality than L*u*v*.

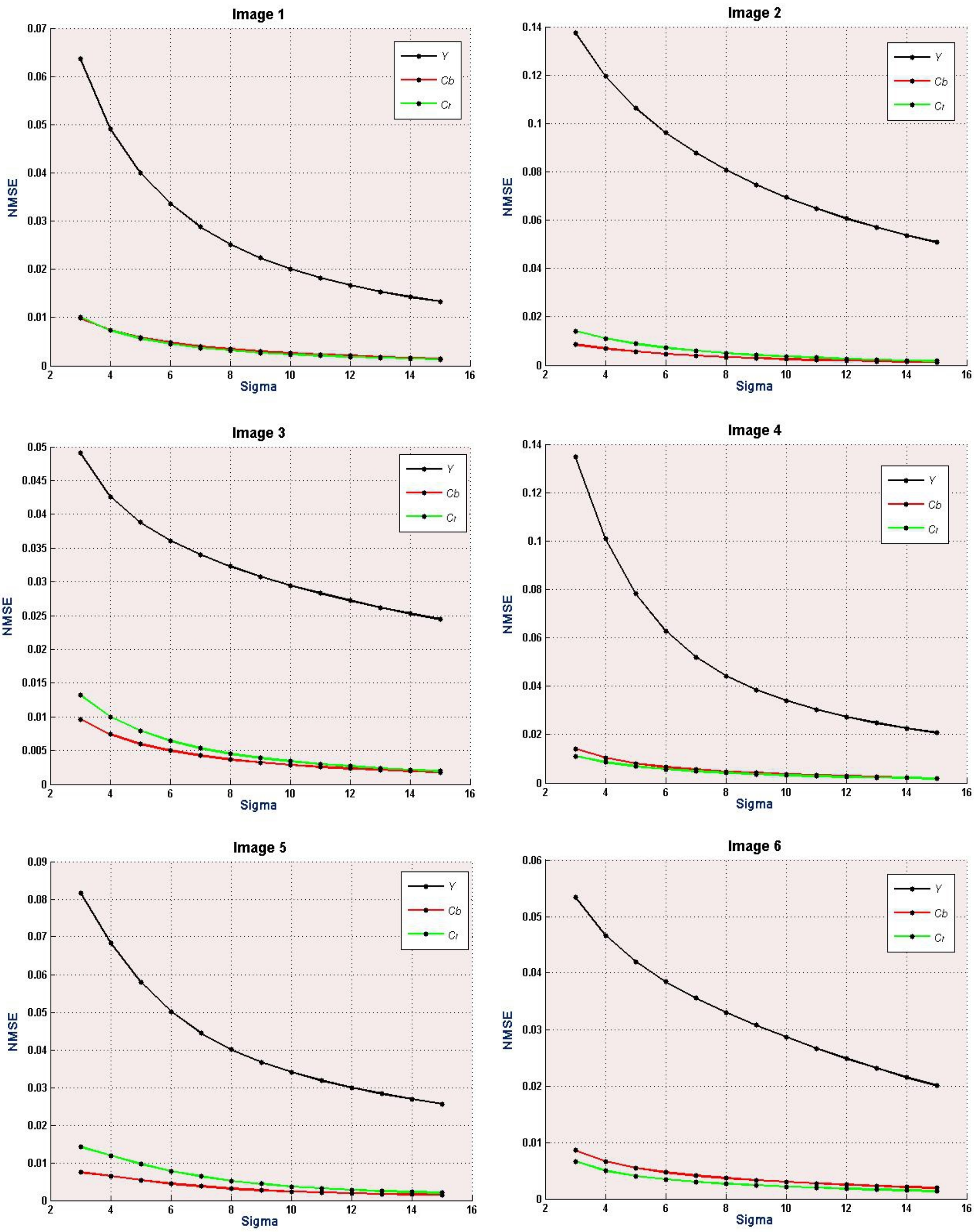

Figure (2)YCbCrcomponentsas a function of sigma in NMSE.

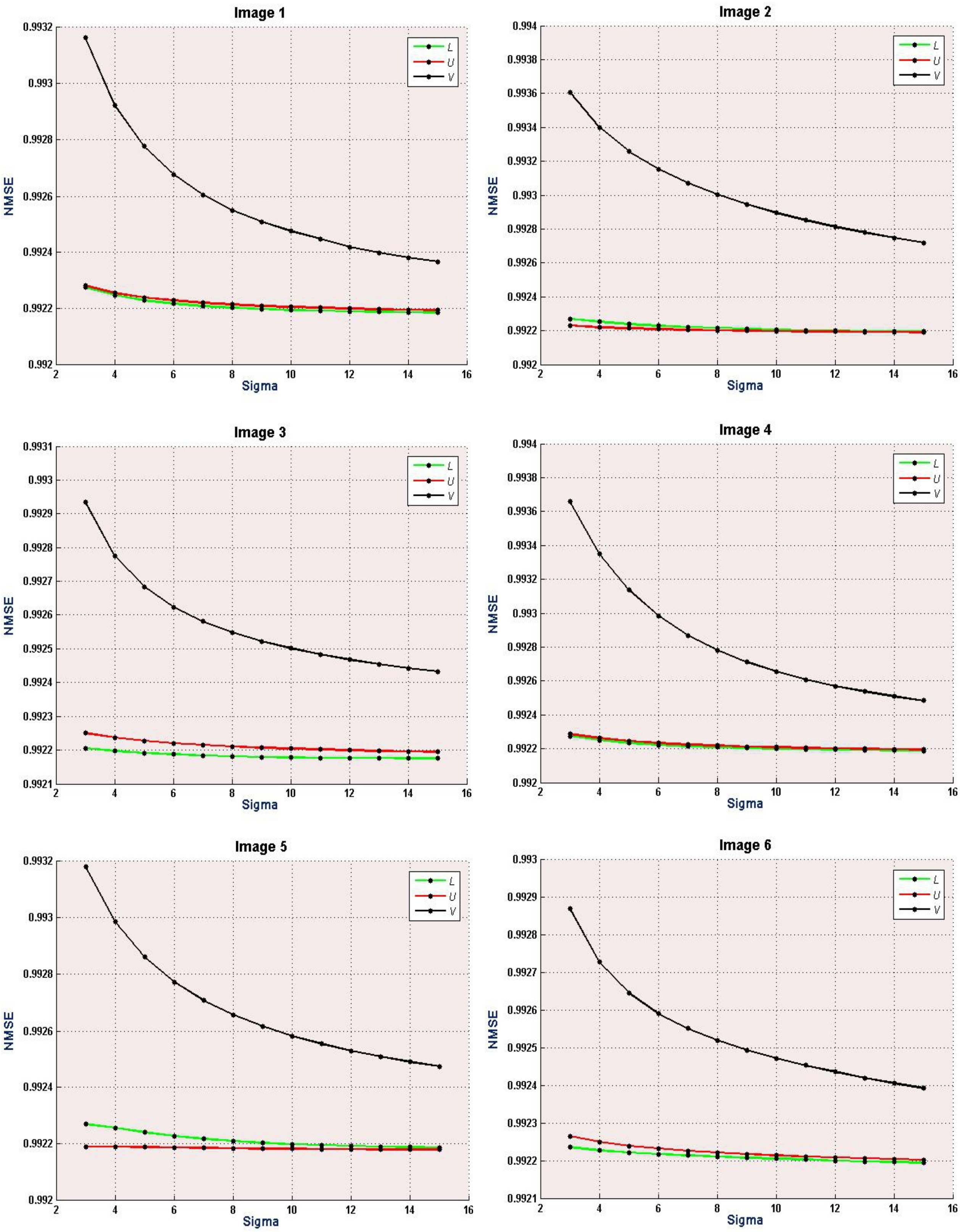

Figure (3)L*u*v*componentsas a function of sigma in NMSE.

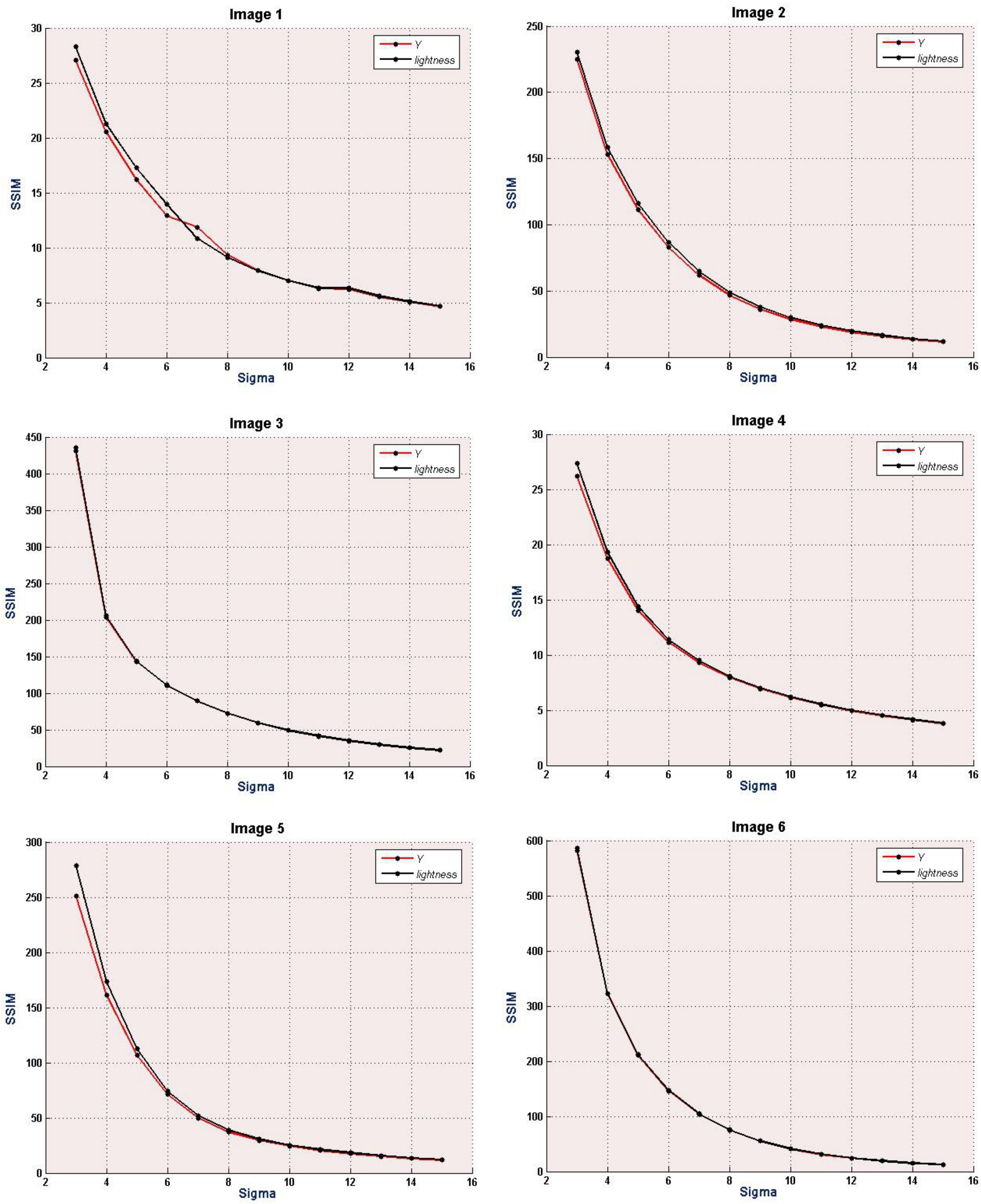

Figure (4)YCbCrcomponentsas a function of sigma in SSIM.

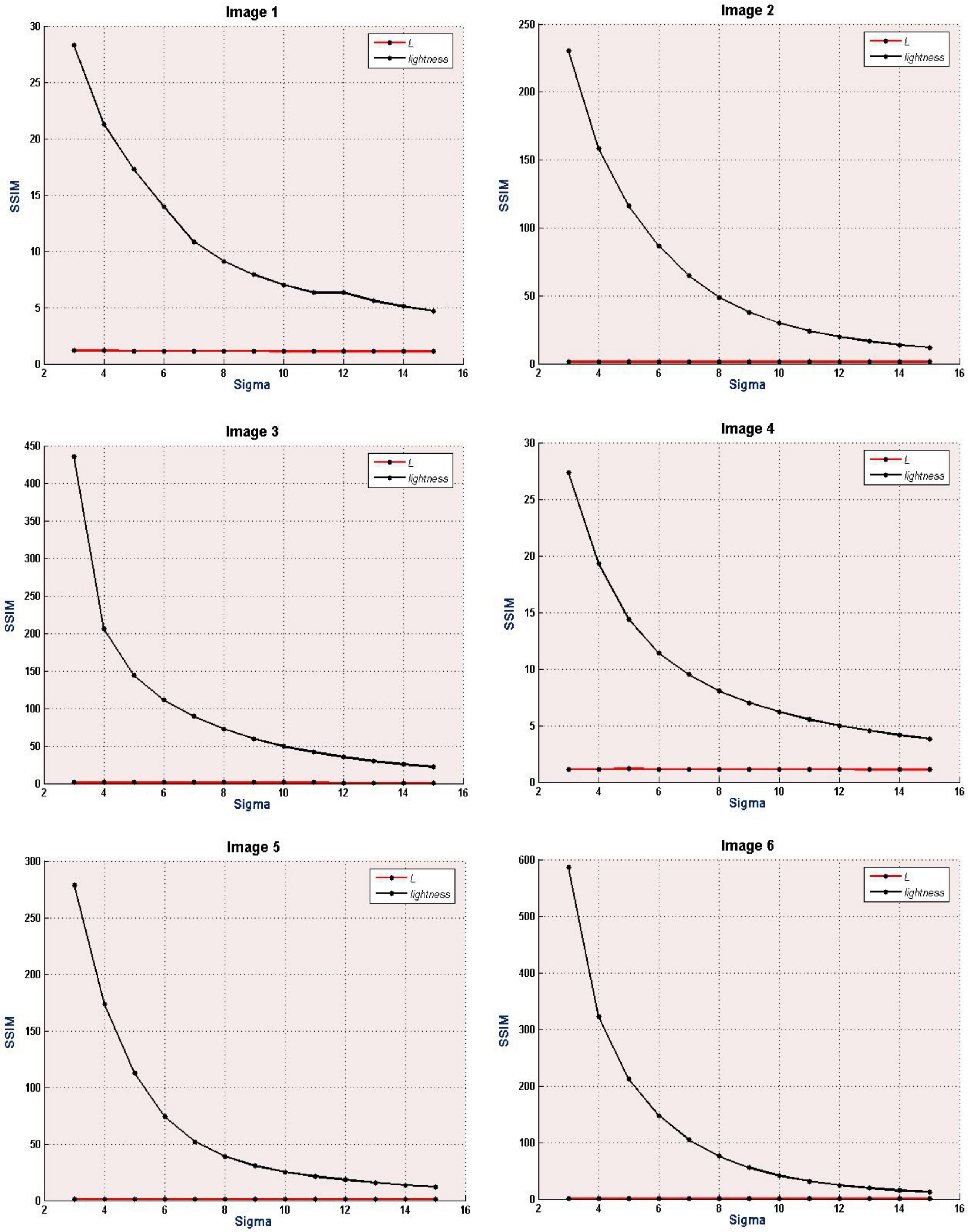

Figure (5)L*u*v*componentsas a function of sigma in SSIM.

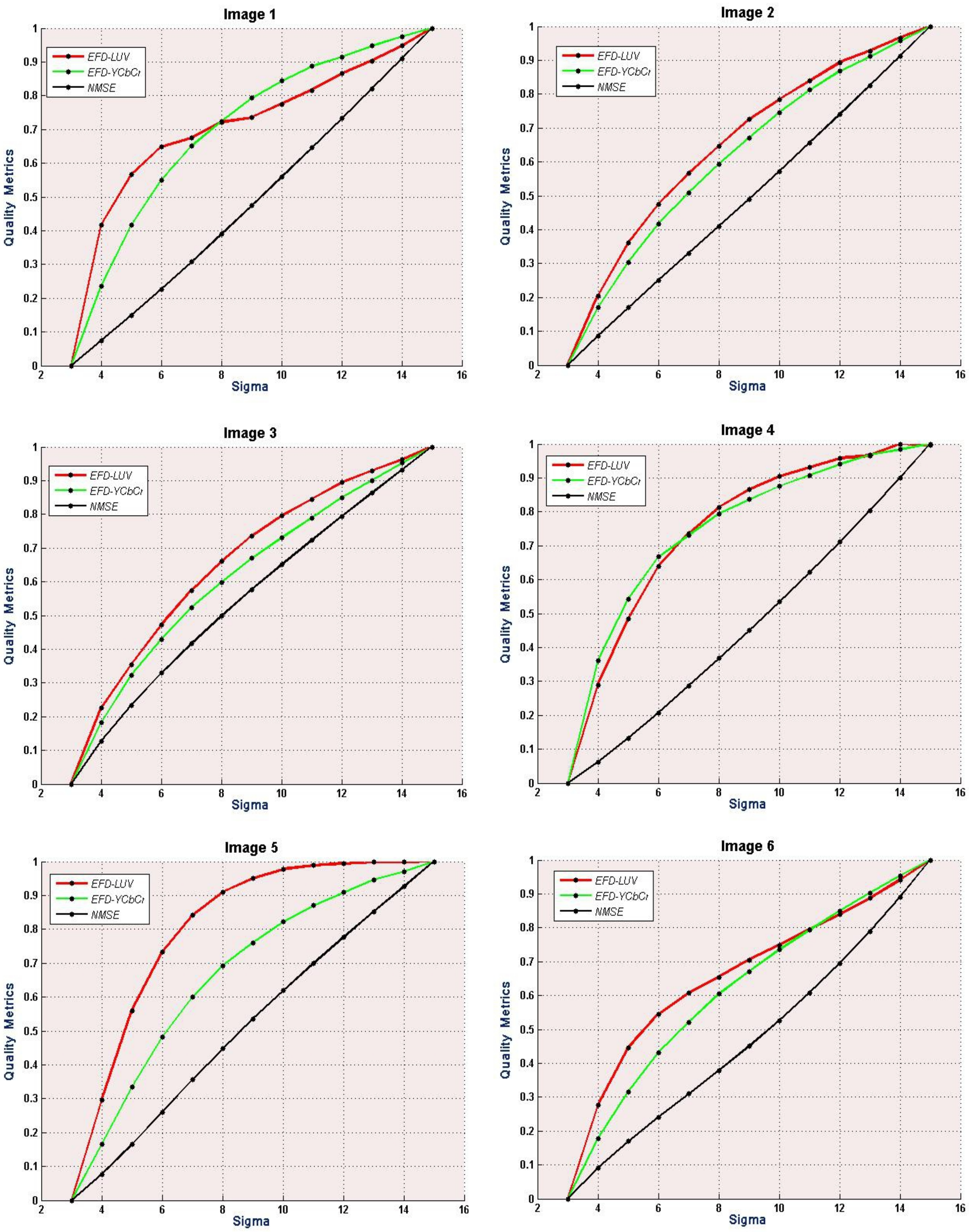

Figure (6)EFD metric in comparing with NMSE as a function of sigma in YCbCr and L*u*v* color spaces.

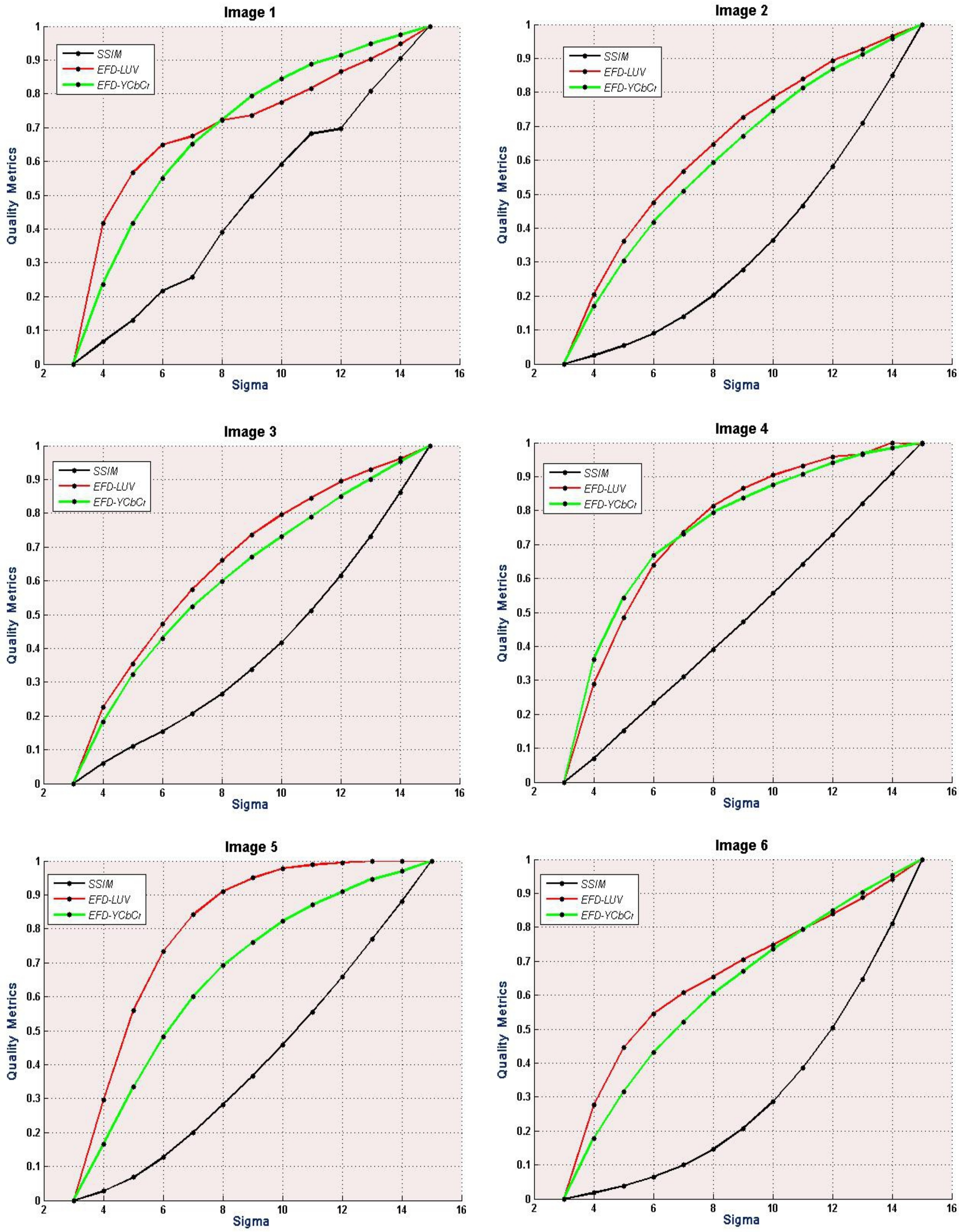

Figure (7)EFD metric in comparing with SSIM as a function of sigma in YCbCr and L*u*v* color spaces..

Table (1): The best color space for quality estimation in EFD metric in comparing with NMSE according to correlation coefficients.

		Image1	Image 2	Image 3	Image 4	Image 5	Image 6	Average Cor.
Correlation coefficients of EFD	**YCbCr**	0.9245	0.9776	0.9825	0.8644	0.9632	0.9667	0.9464
	L*u*v*	0.8823	0.9620	0.9929	0.8695	0.8523	0.9372	0.9160

Table (2): The best color space for quality estimation in EFD metric in comparing with SSIM according to correlation coefficients.

		Image1	Image 2	Image 3	Image 4	Image 5	Image 6	Average Cor.
Correlation coefficients of EFD	**YCbCr**	0.9233	0.9026	0.9270	0.8765	0.8991	0.8643	0.8968
	L*u*v*	0.8744	0.8741	0.8981	0.8817	0.7484	0.8231	0.8499

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