Color to Grayscale Image Conversion Based Dimensionality Reduction with Stationary Wavelet Transform

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***Abstract*—this paper exhibits a brisk and straightforward strategy for changing over coloring pictures to perceptually exact grayscale variants. Strategies performing the transform of color image to grayscale plans to hold however much data about the source color picture as could be expected subsequent to critical picture highlights regularly vanish when color images are convert over to grayscale representation because of dimensionality reduction or varying requirements between the source and target color spaces. In this research we exhibited another complexity improving contrast to grayscale transformation calculation which comprise from procedure steps. Firstly, transform over RGB inputs to a perceptually uniform CIE L*a*b* color space and utilize Helmholtz-Kohlrausch Predictors to corrects L* based on the color chromatic component C* and hue angle H to get enhanced L**. Secondly, Dimensionality Reduction connected to Chrominance channels utilizing key segment investigation. Thirdly, upgrade the resulted grayscale image to the physical luminance channel based on mathematical with α=0.01 to enhance the contrast of resulted grayscale image. At long last, two dimensional Stationary Wavelet Transform (SWT) is connected in one level for melded the came about picture from past stride with Luminosity component L** to get the last grayscale picture. The grayscale image created relied on upon the calculation in the experiment confirm that the calculation has protected the notable components of the shading picture, for example, contrasts, sharpness, shadow, and image structure as contrasted and as compared with recently algorithms.**

Keywords: ***Color image processing; Color to grayscale conversion; Contrast enhancement; Dimensionality reduction; Principal Component analysis (PCA); Stationary Wavelet Transform (SWT).***

I. INTRODUCTION

common applications, for example, printing of reading material and catalogs, reproductions, creative purposes, showing, and visualizing pictures might require a map of the info image from its source color space typically RGB, to an objective color space where the luminance channels is isolated from chrominance channels. Such conversion incorporate changing over color to grayscale image [1]. Regardless of the ubiquity of low-cost storage, computational data transfer capacity, and network bandwidth, grayscale representations stay imperative for some principal image processing and computer vision applications, for example, edge detection, feature extraction, and image and video quality appraisal. On the other hand, numerous laser printers are still highly black-and-white, and the greater part of the photos in day by day daily papers distributed on the world are overwhelmingly grayscale image. One of the main reasons for decolorization process is that intensity or luminance of grayscale image often captures much of the visually important information present in a color image [2]. The procedure of transforming over image from color to grayscale manner can be seen as a mapping or projection from a high dimensional vector space into a lower dimensional space. However, loss of intrinsic data is inescapable because of dimensionality decrease hence, a few colors that are unmistakable in the original image will for the most part be mapped to a solitary intensity in the grayscale image. Consequently, important visual information may be lost in the grayscale conversion process [3]. For example, the contrast between the red sun and the blue background in Fig.1 (a) is lost in its grayscale counterpart in Fig.1 (b). Even though the red and blue colors of the original image are strikingly different, the sun is barely visible in the grayscale version. The essential issue of grayscale transformation that recent color to gray calculations expect to explain is to repeat the aim of the color unique, its complexities and remarkable elements, while preserving the perceived magnitude and direction of its gradients[4].

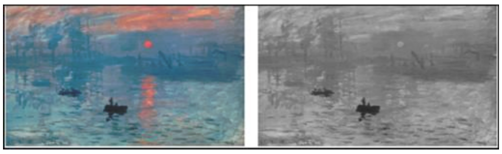

Fig.1 (a) color image (b) standard gray image

Really, perceptually accurate grayscale image is one that emulates both global and local impressions of color image, it matches the base gray level values range and normal luminescence, its local contrasts are neither exaggerated nor understated, its gray values are ordered according to color

appearance and differences in spatial details are imperceptible. Strong perceptual similitude is especially critical for consistency over varying palettes and temporal coherence for animations. We show two-stage greyscale transformation that joins a global mapping based on perceived lightness with a local chromatic contrast enhancement [5]. We apply our technique, Grayscale conversion algorithm to solve the color to gray image issue and build up another decolorization strategy that practically preserve chromatic subtle elements. The primary objective is to preserve the chromatic contrast from the input image as changes in grayscale within the single measurement grayscale axis in a reasonable way. While, the second objective is to keep the yield dark values near the standard grayscale projection so that the yield is a conceivable grayscale transformation of the standard grayscale [4].
The rest of this paper is structured as follows: In Section 2, we first survey the related work. In Section 3 we introduce the Spatial Color to Grayscale Conversion Technique. In Section 4, we present, analyze and discuss the results of the experiments. Finally, in Section 5, we conclude and suggest some ideas for future research.

II. RELATED WORK

There are a few methodologies accessible in the literature that aim to convert over RGB pictures to grayscale utilized a few procedures to outline three dimensional color space to a single dimension. Bala et al. Introduced a method to convert color to grayscale picture by locally protects qualification between adjacent colors by introducing a high frequency chrominance data into the luminance channel and this is refined by applying a spatial high pass mask to the chrominance channels, weighting the yield with a luminance and adding the outcome to the luminance channel. The examinations show the better subjective execution of this methodology over standard procedure L* technique [6]. In 2005 Gooch et al. treated the color to grayscale mapping as an unconstrained optimization issue including local contrasts between neighboring of pixels and attempted to protect the original separation between colors within the mapped grayscale values. The execution of decolorization strategy offer viewers salient data missing from past grayscale image conversion strategies [7]. Ruzon et al. algorithm diminishes the quadratic terms in Gooch et al. Calculations to straight and utilizations clustering and look-up tables to decrease the steady variables and the client has more control over which color are wanted to wind up brighter or darker. Besides, contrast can be improved by scaling chromatic contrasts during the calculation. The subsequent framework is quick, versatile, and simple to utilize [8]. Smith et al. approach utilize two stages for rgb to grayscale mapping first globally assign gray values and decide color ordering utilizing Helmholtz-Kohlrausch color appearance impact for foreseeing contrasts between isoluminant hues, then second, to locally upgrade the grayscale to replicate the original complexity bringing about perceptually exact colorless propagation of the input color [5]. Nguyen et al. propose another polynomial-time grayscale transformation calculation, the yield grayscale images are processed by a compelled quadratic programming scheme utilizing modulation domain components of the information color image. The optimization is formulated such that local color space distance between pixels in the input image are around protected in the yield grayscale image. Experimental producing a grayscale image with better visual qualifications between patches that are close in the color space of the input image [2].

III. COLOR TO GRAYSCALE CONVERSION TECHNIQUE

Take an RGB color image as an input (Ri,Gi,Bi) ∈ $[0,1]^3$, Let Ri, Gi, and Bi represent linear red, green, and blue channels respectively, and the output is a grayscale image ∈ [0, 1] representation. Fig. 2 is a block diagram of our decolorize algorithm has three steps: first, the input color image is assumed to be in a luminance-chrominance representation such as L*a*b*. If the image is in an RGB color space we convert a color image to a perceptually uniform color space such a luminance chrominance representation. Then we present a principal component analysis technique upon chrominance channels (a*,b*) to dimensionality reduction by calculate the color axis that best represents the chromatic contrasts lost when the luminance channel supplies the color to grayscale mapping using PCA. Then, image fusion method applied to combine chrominance information (a', b') by linear time mathematical equation with $\alpha=0.01$ to enhance the brightness of resulted grayscale image. Finally, combined luminance information L** with resulted image from previous step to yield the final grayscale image using SWT.

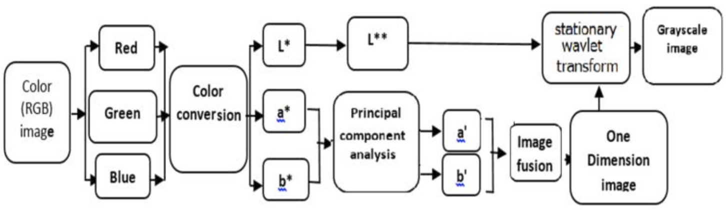

Fig. 2 Block Diagrams of proposed Color Conversion system

A. *Color representation in CIELAB color space*

First convert over the information color image, generally spoke to in RGB space, to be in a luminance-chrominance representation, CIELAB is an opponent color framework implies it oppositional corresponds that some place between the optical nerve and the brain, retinal color boosts are translated into qualifications between light and dark, red and green, blue and yellow[9]. CIELAB shows these qualities with three axes L*, a*, and b* as depicted in fig. 3.

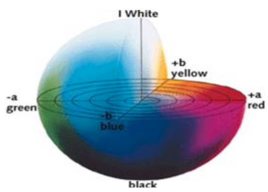

Fig. 3. Three-dimensional CIELAB color

The first segment, L* quantifies the perceptual reaction of a human viewer to luminescence and expansions from the bottom - dark to the top - white of the three-dimensional model. While, the chromatic segments depend on the way that a color can't be both red and green, or both blue and yellow, in light of the fact that these colors restrict one another. On every exes the qualities keep running from positive to negative, On the +a - a pivot, positive qualities show measures of red while negative qualities demonstrate measures of green. On the +b - b axis, yellow is sure and blue is negative. [10]. to change over the measures of red while negative qualities demonstrate measures of green. On the +b - b axis, yellow is sure and blue is negative. [10]. To change over the RGB to CIELAB we firstly, take matrices relating to Red, Green, and Blue can be either somewhere around 0 and 1 or somewhere around 0 and 255, and changes them into XYZ values utilizing Eq. 1

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

At that point we change over XYZ values to L*a*b* color space, the white point needs toward be determined. L* values range from [0; 100] with an estimation of 100 comparing to white point, and a* values range from [-500; 500] and b* values range from [-200; 200]. Given XYZ values and the white point (Xn; Yn; Zn) the L*a*b* qualities are meant as in comparison use Eq.2 [10].

$$L^* = 116\, f(Y/Y_n) - 16$$
$$a^* = 500\, f(X/X_n) - 500\, f(Y/Y_n)$$
$$b^* = 200\, f(Y/Y_n) - 200\, f(Z/Z_n)$$
$$f(w) = (w)^{\frac{1}{3}} \qquad w > 0.008856$$
$$f(w) = 7.787(w) + {}^{16}/_{116} \qquad w \leq 0.008856 \quad (2)$$

Despite the fact that L*a*b* color space is delegated a perceptually uniform space, it is not splendidly direct as for human perception. It is just roughly approximately linear, so we utilize the polar representation L*C* H_{ab} space rather than it. In the L* axis we utilize Helmoltz-Kohlrausch taking into account Fairchild's idea. While a*b* plane is spoken to in polar directions: chromatic C*and hue angle H_{ab}. The Helmoltz-Kohlrausch wonder indicator in light of a chromatic jolt with the same luminance as a white reference stimulus will seem brighter than the reference. We utilize Fairchild model to redress L* in light of the color chromatic parts. Fairchild's CIELAB chromatic lightness metric L** meant by mathematical Eq. 3.

$$L^{**} = L^* + (2.5 - 0.025\, L^*)\left(0.116\left|sin\left({}^{H^\circ - 90}/_{2}\right)\right| + 0.085\right) C^*$$
$$where: \quad C^* = (a*^2 + b*^2)^{\frac{1}{2}}$$
$$and \quad H^\circ = atan\left({}^{b^*}/_{a^*}\right) \quad (3)$$

Chroma C* measures color and a sinusoidal bend predicts the Helmoltz-Kohlrausch impact's diminished effect at yellow hues and its most grounded impact at blue[5]. At last we standardized L**a*b* to get the desired CIELAB color space as in mathematical Eq.4. Fig.3 demonstrated a case of changing over RGB image to CIELAB color space

$$L = {}^{L**}/_{100}$$
$$a = {}^{\left(\left({}^{a*}/_{120}\right)+1\right)}/_{2}$$
$$b = {}^{\left(\left({}^{b*}/_{120}\right)+1\right)}/_{2} \quad (4)$$

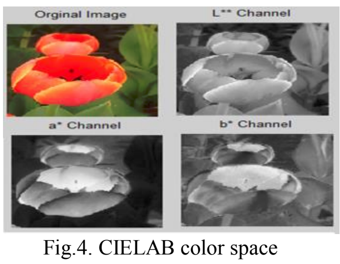

Fig.4. CIELAB color space

B. Dimensionality reduction by principal component analysis

From point of engineering perspective, PCA is characterized as a dimensional decrease strategies which has discovered application in fields, for example, face recognition, image compression, and is a typical strategy for finding patterns in data of high dimension [11]. For instance in data visualization, spreadsheets with a considerable measure of sections are hard to imagine, by decreasing the information to 3 or 2 measurements, we can diagram it. More, in image compression. Really, handling vast images is computationally costly by lessening an expansive picture and as yet safeguarding the basic information in the image that is required for preparing, we can accelerate the preparing and utilize less resources [12]. Regarding math, the fundamental stride of the basic principal component analysis is to develop a covariance framework and process its eigenvalues and eigenvectors. This procedure is comparable to finding the axis in which the covariance array is angled. The eigenvector with the biggest eigenvalue is the direction of most prominent variation, the eigenvector with the second largest eigenvalue is the orthogonal direction with the next highest variation and so on. The formula to figure the covariance matrix given in mathematical Eq.5 which exhibits the low computational unpredictability for large image

$$C = (AA')_{2x2}$$
$$where \quad A = X - M_x \qquad \ldots(5)$$

X = [x1, x2 . . . x_n] represent to an arrangement of two dimensional column vectors of chromatic parts a* and b* got from past area. We utilize the median M_x rather than the mean value to maintain a strategic distance from mistakes brought on by outliers and to standardize the information. Since the information is focused with middle 0.0 and standard deviation 1.0, we register the eigenvalue and eigenvector of the covariance matrix to determine the coefficient matrix which creates the principal components [13] fig.5 show PCA for an image.

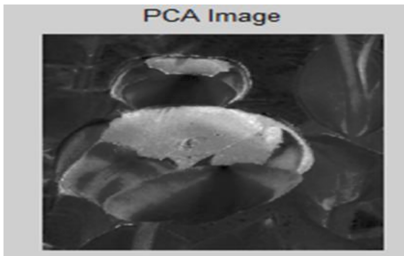

Fig.5. Principal Component Analysis

C. Image fusion of chrominance components

We combine chrominance channels information, since Fused image will be more enlightening and complete than any of the input image. The principal component of chromatic channels a' and b' is gotten and outline to one dimensional chromatic channel F by utilizing expansion operation of the two past channels. To deliver the craved level of contrast enhancement assume α=0.01 as depicted in mathematical Eq.6.

$$F = a' * \alpha + b' \quad (6)$$

At this phase of preparing, the improved chrominance F is grayscale image dependent on linear combination of the original colors RGB mapping linear color grades to linear luminance grades. In spite of the fact that chrominance channels could simply be further improved by standard grayscale methods, since, nonlinear image combination administrator would have more prominent trouble replicating straight coloring inclinations and in this way could be more inclined to false edge artifacts [14].

D. Image Fusion Based Stationary wavelet transform

Images combination is characterized as the procedure of joining two or more diverse images into another single image and holding critical features from every image with broadened data content. This paper proposed an image combination approach in view of 2D Stationary Wavelet Transform SWT. It is like Discrete Wavelet Transform DWT yet somewhat not quite the same as DWT by dropping both down-sampling in the forward and up-sampling in the opposite transform that implies the SWT is interpretation invariant [15]. Similarly as with the decimated algorithm, the low-pass filter and high-pass filter are applied first to the lines and after that to the column. For this situation, in spite of the fact that the created approximation image and detail images are at a large portion of the determination of the original; they are the same size as the input image. The 2-D SWT decomposition scheme represented in Fig.6 where Gi and Hi are a source image, decomposition scheme [16].

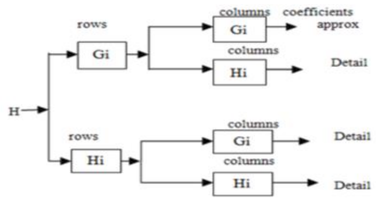

Fig.6. the 2-D SWT Decomposition

in this paper, SWT is initially performed on luminance part L** and the fused image F from past step are decomposed into approximation and detailed coefficients at particular level utilizing SWT, and after that a fusion decision map is created based on a set of fusion rules to combine The approximation and detailed coefficients of both images. The fused wavelet coefficient map can be constructed from the wavelet coefficients of the input images depending to the fusion decision map. At last the combined image is acquired by performing the backwards stationary wavelet transform at indicated level as portrayed in fig.7.

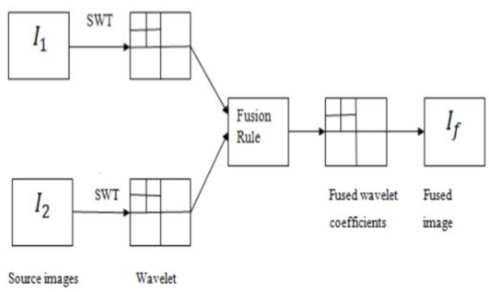

Fig.7. Image fusion scheme based SWT

IV. RESULTS

Our decolorized calculation as appeared in fig.8. Is compelling at improving contrast. We demonstrate the execution of our color to gray transformation in four columns and on wide assortment of color pictures, photos and compare the proposed grayscale system results with the rgb2gray strategy utilizing as a part of Matlab program in column 2 and CIE L luminance channel of CIELAB color space in column 3. We can see from figure the traditional methodology results is on consistent luminance with contrary to what might be expected of our contrast improvement approach that changes the chrominance distinction into well recognizable luminance contrasts, for example, in line 2 of figure the flower brightness ordering is safeguarded and the gray estimations of leaves and background are indistinguishable. Additionally our outcomes grayscale picture in line 3 and line 6 protect all data of color pictures while the pattern is perceptible in their outcomes. Be that as it may, all in all our approach shows improvement over the conventional grayscale representation when attempting to outline spread chrominance degrees to something autonomously recognizable particularly characteristic scenes which regularly have an extensive variety of luminance changes, for example, in very unpredictable pictures as in line 5 the red fish and stone development and the two orange fish reappear in grayscale image. Our transformation technique introduces an undeniable change of the reasonable appearance in the points of interest and preservability of gray image it darkened the green and extremely successful in blue Chroma while utilizing a solid yellow-white chrominance edges to create outlines around the highlighted objects for case in Sunrise picture the sun in sky range of line 1 of fig.7.is well unmistakable in our outcome, while it about vanishes in the traditional grayscale transformation.

V. CONCLUSION

We introduced another quick and more perceptually accurate appearance of color to grayscale mapping technique based on a large number of experiments and observations of the local luminance-chrominance equivalency that working in the CIELAB color space. We have consolidated the H-K impact which consider as basic to acquiring reliable greyscale propagations and a closer reaction to the first color picture. The Experimental results demonstrates that SWT is better image combination strategy when contrasted with PCA and DWT. The principle impediment of our methodology we have not considered changes of chromatic difference because of the connection of the pixel, specifically its appearance regarding its neighboring colors. Later on, we will deliberately survey the calculation execution and we will give more broad experimentation including subjective testing. Really, the best change requires judgment of picture takers and painters. In addition, we will include the multiscale handling to make the proposed technique operate in real-time. Further examination concerning the issue of converting over video to greyscale or to a decreased color set is imperative for video stylization, and more broad experimentation, including the impacts of other image handling capacities, for example, calibration, compression and resolution transformation.

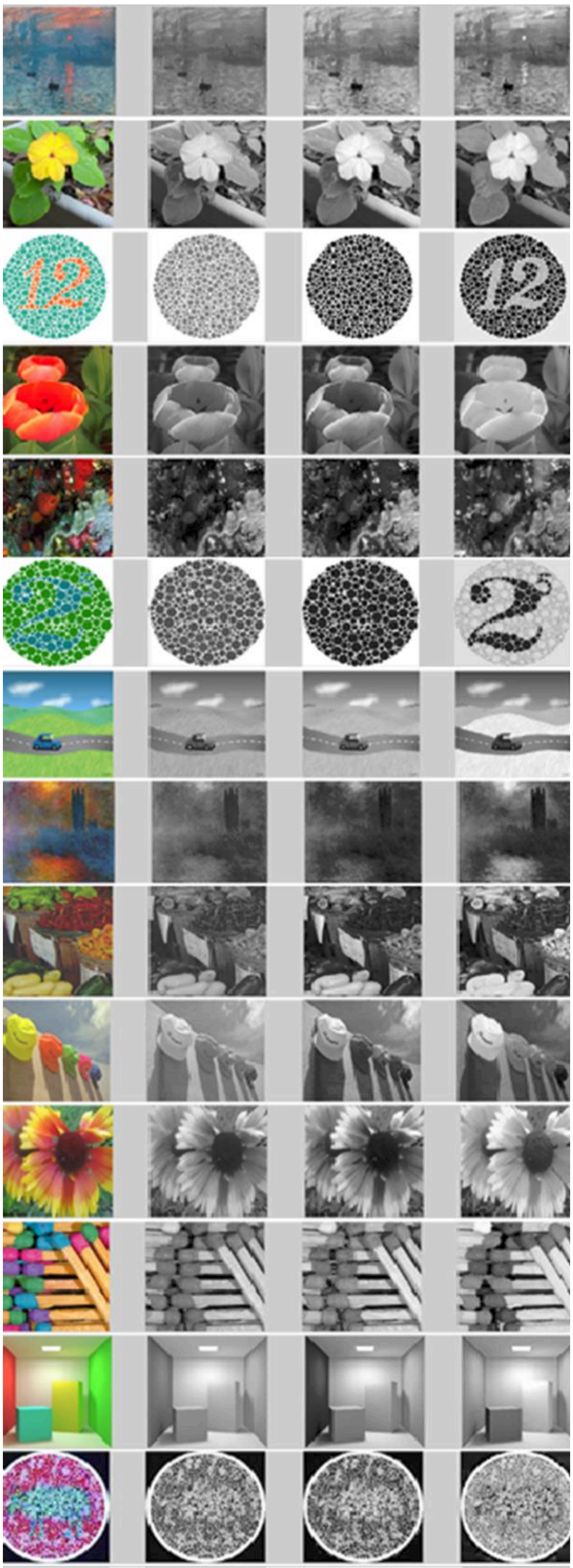

Fig.8. Comparison results of Color Source image, Matlab Grayscale, CIE L* Luminance and our enhanced contrast grayscale conversion method

SUMMARY

We apply our general method of converting color to grayscale image and compare it with some previous existing methods. Our results for color to gray conversion preserve local contrasts from the original image while maintaining the natural colors given by the standard projection. Fig 9 show Comparison of proposed conversion result with other existing methods.

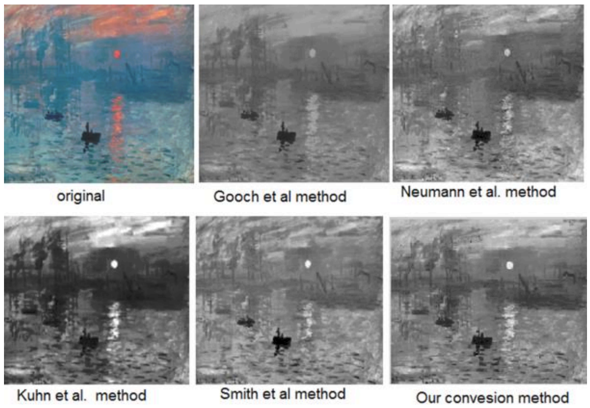

Fig 9. Comparison our method with existing conversion methods

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