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PERCEPTUALLY WEIGHTED COLOR-TO-GRAYSCALE CONVERSION FOR IMAGES WITH NON-UNIFORM CHROMATIC DISTRIBUTION USING MULTIPLE REGRESSION

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Abstract

Color-to-Gray scale conversion methods try to identify weights for various color channels to obtain a gray-scale image. These weights can be fixed either globally or computed on a localized basis. This paper presents an approach for computing the global weights using localized regions perpetually selected based on human perception. The approach aims to bring forth a color invariant gray scale conversion, such that it tries to maximize the required foreground information. The proposed method was tested on DIBCO-2013 dataset and qualitatively evaluated by looking at the structural similarity with the foreground using SSIM. The experimental results of ours and other color-to-gray scale methods have been tabulated and discussed.

Keywords:

Color-to-Grayscale Conversion, Multiple Regression, Least-Square Approach, Color Image, Gray Scale Image

1. INTRODUCTION

The advent of cost-viable and miniaturized semiconductors has enabled sensing and displaying of color images much easier in daily life. Despite such technological advancements, image analysis algorithms utilize Color-to-Gray scale (C2G) conversion. This step, involves reducing a three-dimensional color image to a two-dimensional gray-scale image. Care is taken during such a transformation, so that every indispensable information in the color image is effectively mapped as a gray value.

A color image ($R^{m\times n\times D}$) can be considered as a distribution over three-dimensional integer space. With m and n representing the number of rows & columns respectively, D is the number of color components (or channels). Despite the presence of many other [1] color representations, the color subset perceived by human vision is mapped expeditiously by the RGB color space. The RGB color space model [2] [3], a perceptually dependent color space has been utilized in this paper.

The RGB color model has the three primary colors Red (R), Green (G) and Blue (B) in $R^{m\times n}$ space cascaded one on the other. A pixel in a color image can be expressed as $C\{(i,j),k\}$, such that (i,j) represents the pixel co-ordinates in a $R^{m}\times^{n}$ space and k indicates the color channel ($k \in\{R,G,B\}$). such that ($1<i<m$) and ($1<j<n$).

C2G techniques are visualized as a dimension reduction problems ($R^{m\times n\times 3} \rightarrow R^{m\times n}$), such that every fine detail in the color image is consistently mapped to a unique gray scale value, thereby categorizing these as color variant approaches. A variety of solutions have been experimented on color image datasets for gray scale conversions. Conventional color-to-gray techniques aim to preserve visual and contrast related features at the cost of computation.

In historical document images, contrasting colors have been used to differentiate section titles or important phrases from the main text. A few of them posses degradations thereby hindering even a human reader to perceive text. One of the primary activity prior to analysis and retrieval involves the conversion of color images to its gray scale version. The existing C2G techniques being contrast focused such that it resilience the degradation and other artifacts to the gray scaled image.

Processing such gray-scaled images is a difficult task by the document image analysis and retrieval (DIAR) community. The problem of color-to-gray conversion falls under the domain of natural image processing and has been very minimally examined on historic document images, thereby making it an open issue. To the best of our knowledge, literatures have minimally focused on obtaining effective gray-scale representations for historical document images. Providing a C2G solution that can effectively map vital foreground information can be termed as color in-variant C2G conversion. This paper primarily tries to propose a perceptual computation of weights on localized regions as a color-insensitive gray scale solution. The method reported in this paper tries to identify a normalized global weight using localized regions.

1.1 DATASET USED

With an aim to assess effectiveness of the proposed noise removal C2G conversion, we have used Historic Document Image dataset - DIBCO 2013 [4]. The dataset has a total of sixteen images, with equal numbers in handwritten and printed category. The images are serially numbered separately with the handwritten ones prefixed with 'HW' and the printed versions as 'PR'.

The motive behind choosing these datasets is due to the enormous presence of degradations [5] (bleed-through, inks / stains, character fading, etc.) which are be eliminated for effective segmentation of characters. The Fig.1 shows a few sample images from DIBCO dataset, online repository of Marandog [6], NAMAMI [7] and a personal palm-leaf manuscript collection of Marcel Chowriamah, MSK, Mauritius.

1.2 IMAGE EVALUATION

The classical methods of quantifying the noise present in an images are Peak Signal-to-Noise (PSNR) and Mean Squared Error (MSE). In certain situations [8], these metrics are unable to extract the dominant features for exact quantification.

Structural Similarity Index Matrix (SSIM), a better qualitative and quantitative metric focusing on the structure was established by Bovik [9]. This paper has proposed a C2G conversion method that is color invariant primarily to extract the foreground structure, we have utilized SSIM for investigation.

The rest of the article is organized as follows. Section 2 presents a detailed literature review on a few conventional C2G techniques frequently used by researchers. A short note on pros and cons for each method is also give. Section 3 describes in detail about the proposed approach of weight computation for historic documents. A synopsized description about the algorithm has also been given for quick readers. The experiments carried out using the DIBCO dataset and metrics evaluation using SSIM has been tabulated and discussed in Section 4. A detailed analysis on the computational performance of the proposed approach is also available in this section. In section 5, we summarize our work.

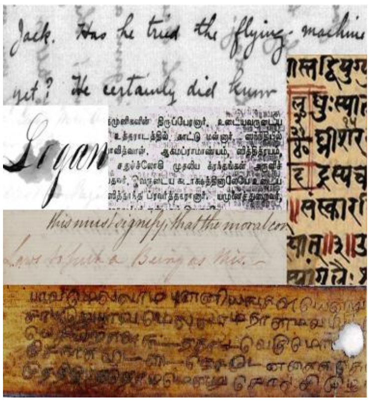

Fig.1. Few samples of Historic Document Images with a variety of degradations

2. PREVIOUS WORK

Chirstopher Kanan [10] has analyzed the effect of a dozen C2G methods for feature extraction on Face Recognition datasets. The methods listed in the above paper have ensured transformation of entire information present in the color image to a gray-scale image. It is important to note that, this entire information also constitutes the noise present in the image. Alexander Toet [11] classified the C2G algorithms into Local and Global mapping methods. With the former aiming at weighing variations of color on a localized basis, the later uses a uniform weight over the entire image. The following sections have concisely dealt with a few C2G techniques used for comparison with the proposed method.

2.1 WEIGHTED GRAYSCALE CONVERSION (WGC)

The most commonly used grayscale conversion is the *rgb2gray* command of MATLAB [12], a Weighted C2G (WC2G) conversion, mathematically expressed as

$$LWGC(i,j) = [0.3.\mathrm{R}(i,j) + 0.59.\mathrm{G}(i,j) + 0.11\ \mathrm{B}(i,j)]\ ,\ \forall(i,j) \quad (1)$$

Where, R,G,B, $LWGC \in \mathrm{R}^{m\times n}$ and R,G,B represents the three primary color channels. Image editing software GIMP uses this method for gray-level transformation.

In this approach, red color possessing a higher wavelength among the three colors has been decreased in its contribution. While the share of green color, with its wavelength less than red and possessing a more soothing effect to the human eyes has been increased. In certain circumstances, this constrain has obstructed the effective intensification of vital information present in red channels.

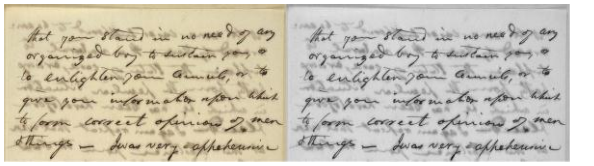

Fig.2. Original Color Image and 'rgb2gray' Gray Image for HW08 - DIBCO 2013 Dataset [SSIM:0.572]

2.2 AVERAGE

Pratt [13] has described the formation of gray-scale image by computing the average of three chromatic components. A few texts have refereed this method as Luminance.

The YUV and YIQ color models used for NTSC, PAL and SECAM television transmissions utilize the above equation for computing the Luminance component (Y). The equation evidently shows that colors have been equally contributed (33%). This increases the visual black components in the gray scale image, thereby consistently mapping the color contrast to gray scale contrast. For the case of Historic Document Images, this mapping shall produce dark artifacts on the gray scale image.

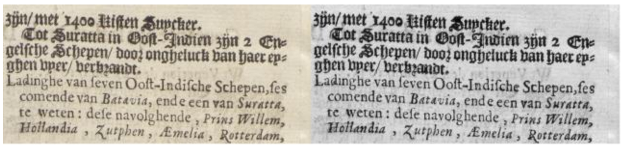

Fig.3. Original Color Image and Average Gray Image for PR07 - DIBCO 2013 Dataset [SSIM:0.583]

2.3 MIN-MAX GRAYSCALE CONVERSION

Another mathematical way of computing the gray-scale value is to compute the average between most and least dominant amongst the three color channels for each pixel [10].

The Fig.4 shows the gray-scale image formed by this method for HW02 named image in DIBCO 2013 dataset. A close look at the output shows a flatter, softer gray scale image. This method exhibits a lower contrast when compared with the WGC method. For document images with varying font colors, there is always a prospect of the more flattering during C2G conversion.

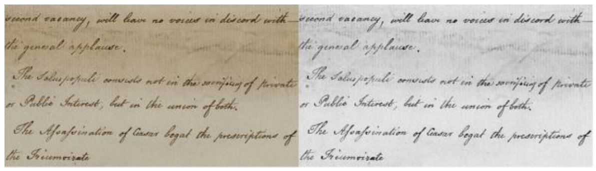

Fig.4. Original Color Image and Min-Max Gray Image for HW02 - DIBCO 2013 Dataset [SSIM:0.682]

2.4 OPTIMIZED SOLUTION FOR C2G

By using simple mathematical techniques, the above three methods have tried to maximize the visual perception features (contrast / brightness) in the perceived gray scale image. Qiu and et al. [14] have tried approaching the dimension reduction problem using optimization theory. The solution would be to maximize one of the first order statistical feature [Variance (σ^2)] of the perceived gray scale image. Micheal [15] improvised the above model by adding up the contrast term to the problem definition. Fig.5, shows the optimized gray scale version for PR02 DIBCO 2013 dataset by maximizing variance and contrast. The approach has provided an optimized solution for gray-scale conversion at the cost of computation.

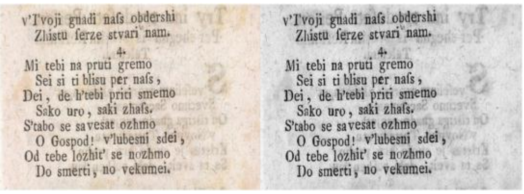
v'Tvoji gnadi nafs obdershi
Zhistu ferze stvari nam.
4.
Mi tebi na pruti gremo
Sei si ti blisu per nafs,
Dei, de h'tebi priti smemo
Sako uro, saki zhafs.
S'tabo se savesat ozhmo
O Gospod! v'lubesni sdei,
Od tebe lozhit' se nozhmo
Do smerti, no vekumei.

Fig.5. Original Color Image and Optimized Gray Image for PR02 - DIBCO 2013 Dataset [SSIM: 0.543]

2.5 SINGLE COLOR CHANNEL VISUALIZATION

For a given $R^{m\times n\times 3}$ space, each color channel can be pictured in an $R^{m}\times^{n}$ space, thereby forming three grayscale images. One such visualization was done by Paramasivam and Sabeenian [16] for images in RGB color space. An alternate method of single color channel visualization is possible for images in $Y\ C_b\ C_r$ [17] color model. The Y channel for PR01 named image in DIBCO 2013 dataset is shown in Fig.6 and can be expressed mathematically as:

$$LYC_bC_r(i,j) = [16+(65.739R(i,j) + 129.057G(i,j) + 25.064B(i,j))],\forall(i,j) \quad (1)$$

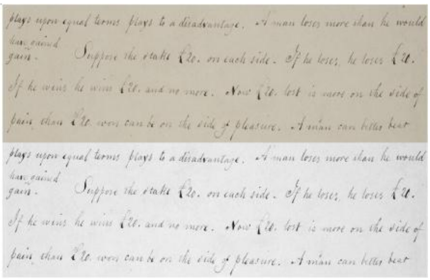
plays upon equal terms plays to a disadvantage. A man loses more than he would have gained
gain. Suppose the stake £10. on each side. If he loses, he loses £10.
If he wins he wins £10. and no more. Now £10. lost is more on the side of
pain than £10. won can be on the side of pleasure. A man can better bear

Fig.6. Original Color Image and YC_bC_r Gray Image for HW01 - DIBCO 2013 Dataset [SSIM:0.871]

We conducted a number of experiments on the DIBCO 2013 dataset and identified that the degradations and color variations normally fall in the green and blue spectrum. This causes most of the above listed approaches producing a highly color variant gray scale image for document images. The SSIM for each of the converted gray-scale image with its corresponding ground truth has been captioned for all the images. Among the listed C2G conversion methods, the single channel visualization YC_bC_r exhibited closeness to ground truth.

3. PROPOSED METHOD

For better understanding, we shall first derive the solution for a system of equations $L = \mathbf{X}\omega$, such that $L \in R^{m\times 1}$, when $\mathbf{X} \in R^{m\times n}$ and $\omega \in R^{n\times 1}$. Conventionally, this equation is an obtained on looking at a small fraction of samples and is considered as general representation of a whole population. Functionally, there shall always be a slight deviation by a nominal value of ε, thereby modifying the generic representation as:

$$L = X\omega + \varepsilon = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ \vdots \\ L_n \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{32} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \\ \vdots \\ \omega_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad (2)$$

In Eq.(2), $\mathbf{X}$ is a non-square matrix vector of size $(m \times n)$, with $m\neq n$ and L a column vector with m components, thereby fashioning the equation $L = \mathbf{X}\omega+\varepsilon$ to a under or over-determined system.

Over-determined System If $m>n$, to determine ω as the best possible fit, Ordinary Least Square Estimator (OLS) try to minimize $\sum_{i=1}^{m}\varepsilon_i$. From Eq.(2), if $\varepsilon = (L-\mathbf{X}\omega)$ the matrix form of minimal error is explicitly represented as $\varepsilon^T\varepsilon = (L-\mathbf{X}\omega)^T(L-\mathbf{X}\omega)$. On equating the first order derivative of minimal error to zero, the solution is obtained as

$$\omega = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^TL \quad ()$$

The second order condition for a minimum, requires that the matrix $\mathbf{X}^T\mathbf{X}$ is positive definite and this is possible only when $\mathbf{X}$ is a full rank matrix.

Under-determined System If $m<n$, the system becomes under-determined and has no unique solution. In such a case we have identified the dominant column and hence utilized the basic solution that has at-most m nonzero components. An elaboration of this has been done with an example in Section 3.2.

$$L = X\omega = \begin{bmatrix} L_1 \\ L_2 \\ L_3 \\ \vdots \\ L_n \end{bmatrix} = \begin{bmatrix} R_1 & G_1 & B_1 \\ R_2 & G_2 & B_2 \\ \vdots & \vdots & \vdots \\ R_M & G_M & B_M \end{bmatrix} \begin{bmatrix} \omega_R \\ \omega_G \\ \omega_B \end{bmatrix} \quad (3)$$

With the elements in matrix $\mathbf{X}$ being linearly independent, the approach is also termed as Multiple Regression. Focusing on images, let $C = [R\ G\ B]$ be a color image defined in $R^{m\times n\times 3}$. The gray-scale image can be obtained using the following mapping:

$$L = \omega_R + \omega_G + \omega_B \quad (4)$$

where ω_R, ω_G and ω_B are weights to be determined for de-colorization of the red, green and blue channels $R\ G\ B$ of C. In the following discussion, we shall express the above equation in matrix form. For a color image $C(R^{m\times n\times 3})$, each color channel is translated into a column vector, such that $\mathbf{X}$ is matrix of size M×3, where M is the total number of pixels in the image.

The column vectors being linearly independent, makes the matrix $\mathbf{X}$, a full rank matrix. For a given full rank matrix $\mathbf{X}$ containing color channels as column vectors and with luminance plane of YC_bC_r as the gray scale matrix L, the system is overdetermined and thus the weights (ω) can be computed using Eq.(6) . The forthcoming part of the paper shall elaborate on how the weights are computed on a localized basis and then normalized for a global mapping.

3.1 LOCAL CHROMATIC WEIGHT MATRIX

This section shall detail on the various steps involved in identifying the Normalized Dominant Chromatic Weight Matrix (NDCWM) from the computed Local Chromatic Weight Matrix

(LCWM). The concept of looking at a sample set and hence estimating weights (ω) for the best fit has been employed. As a first step, we shall constitute (LCWM) from different regions of a color image.

For a given color image ($R^{m\times n\times 3}$), we choose four ($R^{a\times b}$) sample regions such that $a < m$ and $b < n$. We conducted a number of experiments on the DIBCO-2013 dataset for fixing the size of a and b. The following discussion shall give a basic guideline for choosing regions. One important recommendation for sample region selection is to choose regions with minimal noise and maximum foreground (textual) information. The size of the region is ensured that it covers at least one character present in the document image.

We have made use of four sample regions (υ_1, υ_2, υ_3 and υ_4) for estimating four different weights (ω). The size of sample regions chosen in this paper, when tested on the DIBCO 2013 dataset varied from 25×25 to 150×150. A few samples of regions υ_1 and υ_2 extracted from image PR06 of DIBCO-2013 dataset is shown in Fig.7. For each of these extracted sample regions, the gray scale matrix L was computed with values of Luminance plane in $Y\,C_bC_r$ color space. Using Eq.(5), the weights of localized regions (υ_1, υ_2, υ_3 and υ_4) are computed by forming the full rank matrix **X** and the gray scale matrix L.

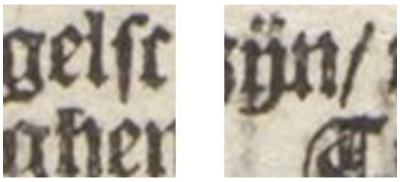

Fig.7. Sample υ_1 and υ_2 regions for image PR06 of DIBCO 2013

3.2 DOMINANT CHROMATIC WEIGHT COMPUTATION

The most dominant color channel can be identified by ranking the mean (μ) for each color channel in $R^{m\times n}$ space. Unlike the weighted gray-scale conversion, our method has tried to weigh color channels perpetually for every image based on the primary color contributions. The weights (ω) obtained from the localized regions (υ_1, υ_2, υ_3 and υ_4) shall reverberate the effect of Equation 4 to a great extent.

Table.1. Computation of Normalized Dominant Chromatic Weight Matrix for the image PR-06

Color Channel	Mean of Color Channel	Weights computed on Localized Regions					Normalized Global Weights
		υ_1	υ_2	υ_3	υ_4	υ_5	
R	200.04	0.0159	0.3197	0.2603	0.086	0.8925	0.4746
G	188.21	0.8416	0.5455	0.6025	0.7638	0	0.4475
B	162.52	0.1465	0.0594	0.0708	0.1080	0	0.0779

With a motive to extract maximum information from the dominant chromatic channel, we have estimated weights using a single pixel from the color image. This single pixel used for computation is considered as region '$\upsilon 5$' in the proposed method. Representing **X** using a single pixel value from color image shall be rank deficient. An example briefing on the method used for working with a rank deficient matrix has been given below.

Consider a color pixel value expressed in the form of **X** = [255 243 210]. Let the corresponding gray-scale value in the YC_bCr plane at the same pixel location be L = 208.

Expressing these in matrix form:

$$\begin{bmatrix}255 & 243 & 210\end{bmatrix}.\begin{bmatrix}\omega_R\\ \omega_G\\ \omega_B\end{bmatrix} = 208 \tag{5}$$

The above equation depicts an under-determined system with no unique solution. Analysis on values of the pixels indicate that the first column has the highest value, thereby indicating the most dominant color channel. To emphasize the dominant color in the color image, we shall make the variables ω_G and ω_B as free variables (assigning '0' to ω_G and ω_B in Eq.(9)). The basic solution thus becomes $[0.8157\ 0\ 0]^T$, thereby making ω contain only one nonzero element.

Normalized Dominant Chromatic Weight Matrix The maximum weight for each color channel is evaluated from the local weights of the five regions (υ_1, υ_2, υ_3, υ_4 and υ_5). These weights are then normalized between 0 and 1. The Table.1 shows the computed local weights and normalized global weight for the image PR-06. On referring to the mean of each color channels, the weights obtained apparently duplicate the contribution of color channels in RGB space.

3.2.1 Synopsized Steps for Proposed Algorithm:

Step 1: Local Chromatic Matrix Computation

(a) Repeat Steps (b) to (e) for four different regions on the color image to obtain weights for four regions (υ_1, υ_2, υ_3 and υ_4).

(b) Extract a sample region from document image in RGB color space Guidelines for Sample Extraction :

i. Size of the sample to cover at-least one character in the document image.

ii. Regions with maximal foreground (textual) information and minimal degradation (noise) are to be focused.

(c) Transform the color channels to column vectors to form a full rank matrix **X** of size $M \times 3$, where M is the total number of pixels in the sample.

$$\mathbf{X} = \begin{bmatrix} R_1 & G_1 & B_1\\ R_2 & G_2 & B_2\\ \vdots & \vdots & \vdots\\ R_M & G_M & B_M \end{bmatrix} \tag{6}$$

(d) For the sampled region, convert from RGB to YC_bC_r color space and extract the Luminance plane. Transform these gray values to form the gray scale matrix L of size M ×1.1T

(e) Compute weights ω using the equation $\omega = (\mathbf{X}^T\mathbf{X})$-$\mathbf{X}.L$.

(f) Extract any one pixel from the color image and determine a basic solution by identifying the column with highest value. Region (υ_4).

(g) These five weight matrices form the Local Chromatic Weight Matrix.

Step 2: Normalized Dominant Chromatic Weight Matrix

(a) Identify the maximum weights amongst the five values for every color channel.

(b) Normalize the obtained values between 0 and 1. This is the Normalized Dominant Chromatic Weight Matrix (NDCWM)

Step 3: Apply the computed (NDCWM) on the color image C in RGB color space to obtain the gray scale image.

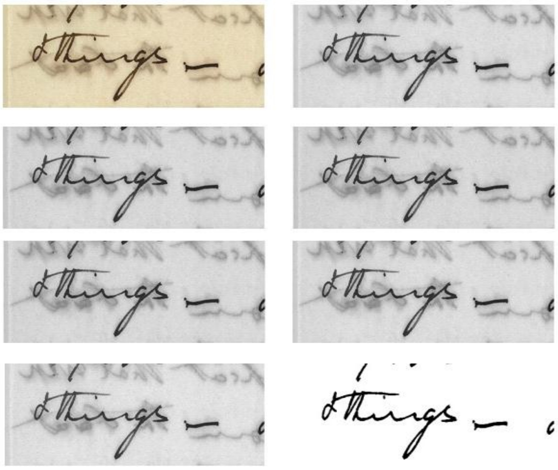

Fig.8. Small portion of image PR02 in DIBCO 2013 dataset (From top-left corner in anti-clockwise: Original Image, WGC, Min-Max, Micheal Ng [15], Ground Truth, Luminance of YC_bC_r Color Plane, Average. The bleed-through close the word 'things' has been reduced to a great extent in the proposed approach when compared to other approaches)

4. EXPERIMENTS AND DISCUSSIONS

We have made use of the historic document image dataset DIBCO-2013 for evaluating the proposed approach. DIBCO contests were targeted to develop competitive algorithms that shall help in efficient binarization and thus support competent segmentation. The proposed method focuses on a color invariant C2G conversion and hence, we have utilized dataset. For the sake of comparison, the C2G methods described in Section 2 have been computed on all sixteen images of DIBCO-2013 dataset.

The Table.2 and Table.3 contains the values of SSIM for Weighted Gray-scale Conversion, Average, Min-Max, YC_bC_r, Micheal [15] and the proposed C2G methods computed with ground truth. The proposed method has exhibited higher values of SSIM when compared to other C2G techniques.

Table.2. SSIM Comparison Chart for various C2G conversion on Handwritten DIBCO images

HW01	**HW02**	**HW03**	**HW04**	**HW05**	**HW06**	**HW07**	**HW08**
0.87442	0.70976	0.75623	0.45755	0.46749	0.74724	0.79990	0.54611
0.87267	0.69744	0.75571	0.45755	0.46749	0.74724	0.79990	0.54229
0.87400	0.71245	0.74355	0.45755	0.46749	0.74724	0.79990	0.49166
0.87114	0.68583	0.75358	0.45755	0.46749	0.74724	0.79990	0.52792
0.87311	0.69309	0.76302	0.45755	0.46749	0.74724	0.79990	0.54290
0.87021	0.70901	0.75038	0.45646	0.46741	0.74683	0.79595	0.54567
0.88849	0.72145	0.76900	0.45755	0.46749	0.74724	0.79595	0.58000

Table.3. SSIM Comparison Chart for various C2G conversion on Printed DIBCO images

PR01	**PR02**	**PR03**	**PR04**	**PR05**	**PR06**	**PR07**	**PR08**
0.53736	0.54229	0.74524	0.63962	0.65420	0.60592	0.59295	0.46661
0.53141	0.53938	0.73790	0.63525	0.64800	0.59974	0.58300	0.45417
0.59773	0.51428	0.74407	0.65757	0.65247	0.60352	0.60887	0.49414
0.53412	0.53495	0.73760	0.62801	0.64180	0.58911	0.57807	0.44947
0.57032	0.54011	0.73805	0.63377	0.64885	0.60372	0.58463	0.46022
0.53819	0.54383	0.74484	0.63939	0.65304	0.60460	0.59259	0.46644
0.61959	0.54493	0.74908	0.65959	0.65508	0.64023	0.60956	0.52450

The Table.2 and Table.3 demonstrate that the new method provides structurally better results when compared to other C2G methods, particularly for historic document images containing enormous noise. To justify the allocation of weights for each of the color channels based on its dominance in $R^{m \times n \times 3}$ space, we have tabulated (Table.4) the weights along with its corresponding mean of each color channel in $R^{m \times n}$ space. It is evident that the weights have been fixed based on the individual contribution of the color channels.

Table.4. Weights computed by the proposed method and Mean for each color channel of images in DIBCO2013 dataset

File Name	**SSIM**	ω_R	ω_G	ω_B	μ**R**	μ**G**	μ**B**
HW01	0.88849	0.62345	0.34123	0.03532	195.61	188.16	171.861
HW02	0.72145	0.70369	0.23124	0.06507	177.02	163.95	140.50
HW03	0.76900	0.60918	0.3385	0.05232	200.31	191.38	178.74
HW04	0.45755	1	0	0	197.46	197.46	197.46
HW05	0.46749	1	0	0	216.49	216.49	216.49
HW06	0.74724	1	0	0	229.68	229.68	229.68
HW07	0.79595	1	0	0	209.35	209.35	209.35
HW08	0.58	0.57434	0.3885	0.03716	205.88	192.45	159.55
PR01	0.61959	0.56634	0.38953	0.04413	185.2652	167.19	143.43
PR02	0.54493	0.57167	0.37463	0.0537	217.38	204.97	192.05
PR03	0.74908	0.2393	0.71294	0.04776	197.10	216.24	190.90
PR04	0.65959	0.65655	0.3193	0.02415	193.10	179.89	162.07
PR05	0.65508	0.50806	0.39175	0.10019	193.56	185.14	174.09
PR06	0.64023	0.47459	0.44753	0.07788	200.04	188.21	162.52
PR07	0.60956	0.48081	0.37337	0.14582	192.82	183.51	164.83
PR08	0.52450	0.5543	0.42643	0.01927	209.21	17762	119.11

Consider the case of HW03, the computed weights are $[0.60918\ 0.3385\ 0.05232]^T$. Looking on mean of each color channel, the highest is spondingly weight $\omega_R = 0.60918$ also is the highest among the three weights. Other two value uses are noticeably varying with reference to the mean values ($\mu_G = 191.38$ and $\mu_B = 178.74$).

Computation Time the algorithms were executed on an Intel®Core™i5-4210U CPU @ 1.70GHz 2.40GHz with 4GB RAM and 64 bit Windows 8 platform. The computation time of each above method in Section 2 and proposed method was also calculated. The authors have carried out this comparison not to humiliate the poor performance of previous approaches, but to emphasize that a perceptual approach is more computationally efficient. The results shows that the proposed multiple regression fetching the least computation time when compared to others.

4.1 LIMITATIONS OF THE METHOD

For images HW04, HW05, HW06 and HW07 the contribution of each color channel is equal. In such a case, the proposed method does not suit and the weights have be contributed only for one color channel.

5. CONCLUSIONS

We have presented a color-invariant color-to-gray scale conversion algorithm that uses Multiple Regression technique perceptually over different parts of the image. The method has proved to provide adaptive weights relatively depending on the contribution of each color channel. The results obtained by such methods are satisfactory both on a subjective and quantitative basis. The Table.2 clearly shows that the computed weights ω_R, ω_G and ω_B are progressive with respect to the individual color channels, indicated by mean values. The performance of the proposed approach largely depends on the regions choose for computing the weights. We conducted a number of investigations on the dataset and identified the best possible regions for computing the weights. The marginal performance of certain images is due to the marginal chromatic contribution between color channels.

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