Comparative Study of Different Color Normalization and Contrast Enhancement Techniques

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Abstract— Image enhancement goes for enhancing the nature of picture for better perception. The objective of color and contrast enhancement, as a rule, is to give an all the more engaging picture or video with clear hues and clarity of subtle elements. These improvements are personally identified with distinctive properties of visual sensation. It is essential to characterize these qualities before examining the goals of shading and complexity upgrade, or the different strategies to accomplish them. To achieve this, we propose several algorithms for color normalization. Four such algorithms have been discussed in the paper namely Gray World Assumption, Retinex Theory, Diagonal Theory and Quadratic Mapping of Intensities. Also, three Contrast Enhancement techniques have been talked about. They are Histogram Equalization Algorithm, Contrast Stretching algorithm, Local Enhancement Using Histogram Statistics, and Colour Deconvolution. Also, it has been demonstrated that which algorithm works better in which scenario. The objective of contrast enhancement is to build the visibility of subtle elements that might be darkened by insufficient worldwide and nearby lightness.

Key words: Contrast Enhancement Techniques, Color Normalization

I. INTRODUCTION

An image taken from a stained blood sample utilizing a conventional light microscope has many elements which might influence the observed colors of the plasma (background), cells, and stained objects. These conditions might be because of the microscope components like different color features of the intensity adjustments, light source, or color filters. However, color differences are mainly related to the differences in the slide preparation process: different stain concentrations, different staining durations, or non-uniform staining. Thus, standardization of the blood film preparation itself is also required. The color normalization for the peripheral thin blood film images is aimed at producing images which do not differ in their color characteristics i.e. are normalized. After normalization comes enhancement. Several techniques have been implemented and the best one is taken into consideration for both (color normalization and image enhancement).All the algorithms have been implemented in Matlab 7.10.0(R2010a).

II. COLOR NORMALIZATION TECHNIQUES

A. Gray World Assumption

It argues that for a typical scene, the average intensity of the red, green, and blue channels should be equal. This method is very important for imaging, where the average is directed towards darker regions of the region of interest which tend to be neutral. In terms of implementation, let an image I(m,n) have size A × B, where m and n denote the indices of the pixel position. Furthermore, let Ir(m,n), Ig(m,n), and Ib(m,n) denote the red, green, and blue channels of the image respectively. We compute

$$R_{\text{avg}} = \frac{1}{\text{AB}} \sum_{\text{m=1}}^{\text{A}} \sum_{\text{n=1}}^{\text{B}} \text{I}_{\text{r}}\,(\text{m},\text{n})$$

$$\text{G}_{\text{avg}} = \frac{1}{\text{AB}} \sum_{\text{m=1}}^{\text{A}} \sum_{\text{n=1}}^{\text{B}} \text{I}_{\text{g}}(\text{m},\text{n})$$

$$\text{B}_{\text{avg}} = \frac{1}{\text{AB}} \sum_{\text{m=1}}^{\text{A}} \sum_{\text{n=1}}^{\text{B}} \text{I}_{\text{b}}(\text{m},\text{n})$$

In the event that the three values are indistinguishable, the image already fulfills the gray world assumption. Generally, they might not be. Commonly, we keep the green channel unaltered and denote the gain of the red and blue channels

$$x = \frac{G_{avg}}{R_{avg}} \quad \text{And} \quad y = \frac{G_{avg}}{B_{avg}}$$

Then the red and blue pixels are adjusted by

$$\widehat{I_r}(m,n) = xI_r(m,n)$$
$$\widehat{I_b}(m,n) = yI_r(m,n)$$

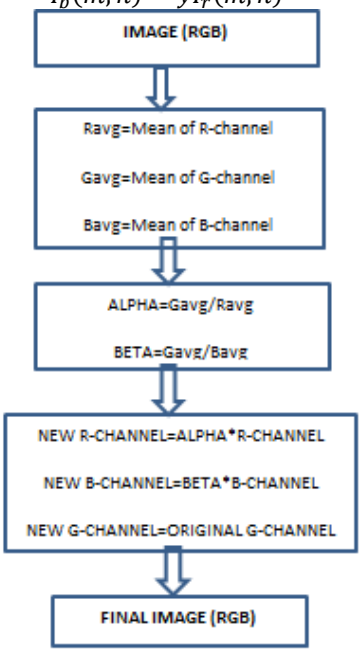

Fig. 1: Flowchart for grayworld assumption

B. Retinex Theory

Under the Retinex theory, it is contended that the apparent white is connected with the maximum cone signals of the human visual system. As such, the strategy for white balance should be to equalize the extreme values of the red, green, and blue channels. To prevent disturbances to the computation resulting from by a few bright pixels, one can treat clusters of pixels or lowpass the image. To implement this, we calculate

$$R_{max} = \max_{m,n}\{I_r(m,n)\}$$
$$G_{max} = \max_{m,n}\{I_g(m,n)\}$$
$$B_{max} = \max_{m,n}\{I_b(m,n)\}$$

Like the gray world assumption, we maintain the green channel unaltered. The gain for the red and blue channels is defined as

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$$x = \frac{G_{max}}{R_{max}} \quad and \quad y = \frac{G_{max}}{B_{max}}$$

The red and blue pixels is then adjusted by

$$\widehat{I_r}(m,n) = xI_r(m,n)$$

$$\widehat{I_b}(m,n) = yI_b(m,n)$$

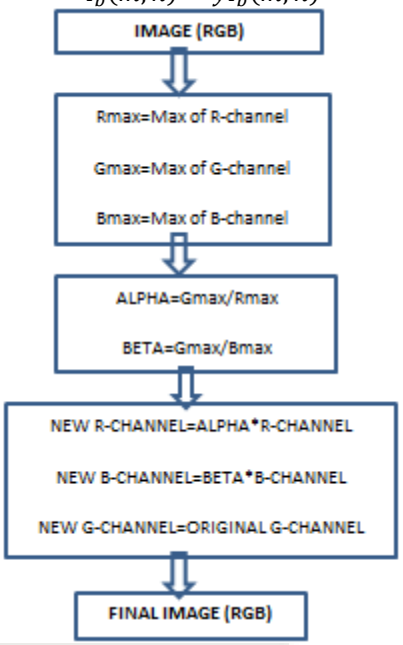

Fig. 2: Flowchart for Retinex theory

C. *Quadratic Mapping of Intensities*

The two methods have their separate qualities. For most images, the two techniques produce diverse results. In other words, the amended image can rarely fulfill both the gray world assumption and the Retinex hypothesis. Moreover, there is likewise a fixed point in the mappings: for pixels with zero intensity, the two mappings would not influence their qualities. To include the justifications of both methods, we propose a simple adjustment here with a quadratic mapping of intensities. Similarly as with the strategies above, we keep the green channel unaltered.

Let the change to the red channel be depicted as

$$\breve{I_r}(m,n) = u{I_r}^2(m,n) + vI_r(m,n)$$

Where (u, v) are the parameters for automatic white balance. To satisfy the gray world assumption, we require that

$$\sum_{m=1}^{A}\sum_{n=1}^{B} \breve{I_r}(m,n) = \sum_{m=1}^{A}\sum_{n=1}^{B} I_g(m,n)$$

i.e.

$$u\sum_{m=1}^{A}\sum_{n=1}^{B} {I_r}^2(m,n) + v\sum_{m=1}^{A}\sum_{n=1}^{B} I_r(m,n) = \sum_{m=1}^{A}\sum_{n=1}^{B} I_g(m,n)$$

Additionally, to fulfill the Retinex theory, we need

$$u\max_{m,n}\{{I_r}^2(m,n)\} + v\max_{m,n}\{I_r(m,n)\} = \max_{m,n}\{I_g(m,n)\}$$

We can depict the above-mentioned two equations in a matrix form:

$$\begin{bmatrix} \sum\sum {I_r}^2 & \sum\sum I_r \\ \max {I_r}^2 & \max I_r \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum\sum I_g \\ \max I_g \end{bmatrix}$$

This is solved analytically, either with Gaussian elimination or using Cramer's rule. The white balance for the blue channels can be computed in an analogous manner.

D. *Diagonal Method*

The "diagonal model" is a simple and satisfactory model which assumes that there is a diagonal 3x3 linear transformation matrix which maps (pc = Mpu) the RGB response under an unknown illuminant pu = (ru; gu; bu) to the RGB response under a canonical known illuminant pc = (rc; gc; bc).

When the transformation matrix is assumed to be Diagonal, its non-zero elements (mii) can be calculated by simple scaling pci/pui

Where i E {r; g; b}.

$$M = \begin{bmatrix} m_{rr} & 0 & 0 \\ 0 & m_{gg} & 0 \\ 0 & 0 & m_{bb} \end{bmatrix}$$

The simple gray value assumption can be incorporated into the color normalization process of thin blood films. Be that as it may, at first, input images must be separated into foreground and background regions.

After separating the input (Iui) channels (i.e. {r; g; b}), foreground (Ifur; g;b) and background (Ibui) images are obtained and the proposed color normalization is performed as follows:

1) Calculate $({I_{b_i}}^u)$channel averages.Calculate $M^b: m_i^b = \frac{255}{\mu^{I_{b_i}^u}}$
2) Transform the whole image: $I^1 = M^b I^u$ with eq.
$$m_i = \frac{G_i}{\mu_i^u}\left(\mu_i^u = \frac{1}{N}\sum_N I_i^u\right) \text{ (i={r,g,b})}$$
3) Calculate: $M^f: m_i^f$ using eq. $m_i = \frac{\mu_i^c}{\mu_i^u}$ With $(I_{f_i}^1)$ and the reference image foreground channels $(I_{f_i}^c)$
4) Transform only the foreground channels: $I_f^2 = M^f I_f^1$
5) Replace the foreground channels of I^1 with I_f^2 to obtain the final color normalized output imageI^2.

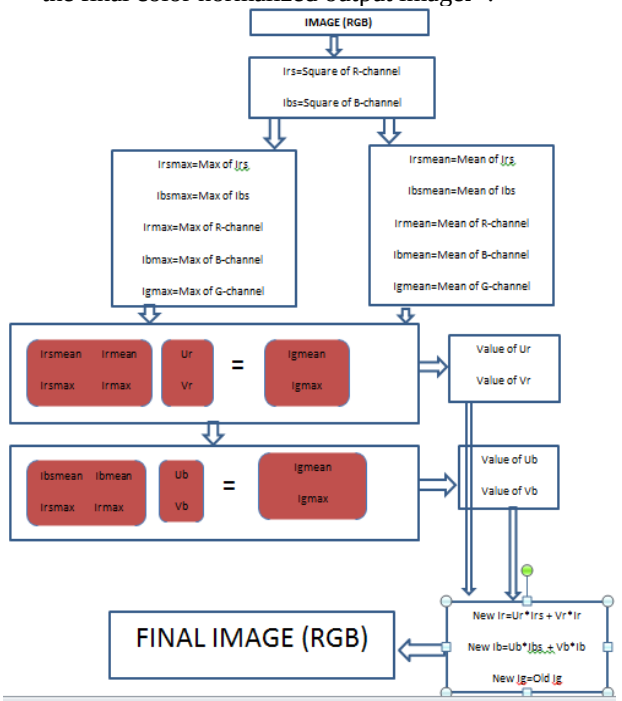

Fig. 3: Flowchart for quadratic mapping of intensities

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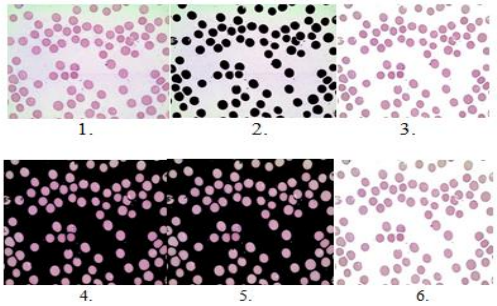

Fig. 4: Performance of Diagonal Matrix approach ((1) Input, (2) Background image, (3) Background corrected image, (4) Foreground image, (5) Foreground corrected image, (6) Final output)

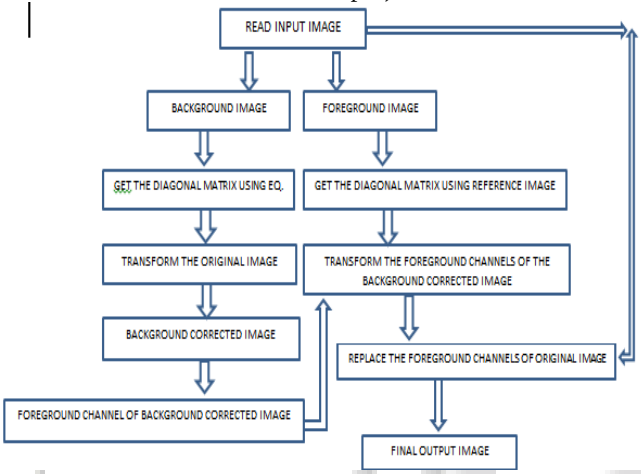

Fig. 5: Flowchart for diagonal matrix approach

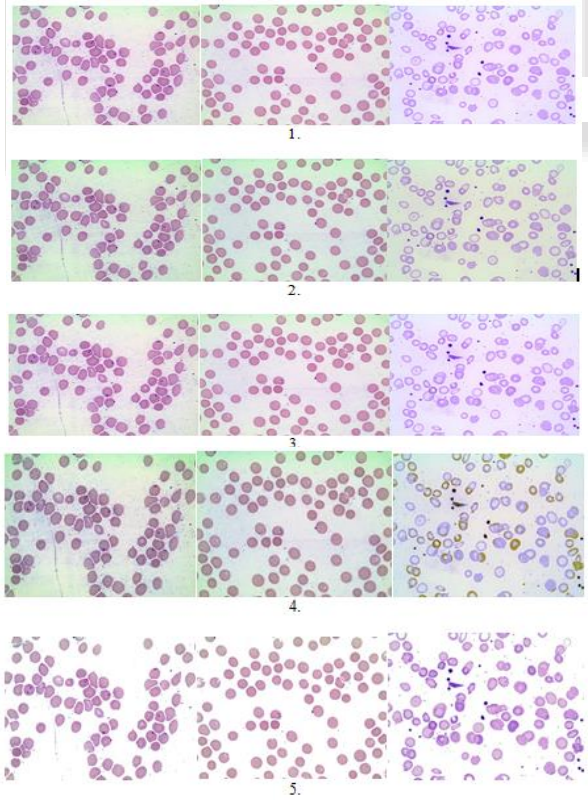

Fig. 6: Comparison of different color normalization techniques (1)Input images , (2) Output images for grayworld assumption, (3) Output images for Retinex theory, (4) Output images for quadratic mapping , (5) Output images for diagonal matrix approach

III. CONTRAST ENHANCEMENT

A. Histogram Equalization Algorithm

The general form is

$$S_k = \frac{(L-1)*(r_k - r_{kmin})}{r_{kmax} - r_{kmin}}, \text{ k = 0, 1,2….L-1}$$

Where r and s are defined as the input and output pixels for the image or picture, L is the distinctive values that can be the pixels, and rkmax and rkmin are the greatest and least gray values of the input image.

This method normally builds the global contrast of images, particularly when the usable information of the image is spoken to by close contrast values. Through this change, the intensities can be better disseminated on the histogram. This takes into consideration regions of lower local contrast to gain a higher contrast. Histogram equalization achieves this by viable spreading out the most incessant intensity values.

The technique is helpful in images with backgrounds and foregrounds that are both bright or both dark. Specifically, the method can prompt better detail in histological images that are more or under-exposed. An important benefit of the method is that it is a straightforward and direct technique and an invertible operator. So in principle, if the histogram equalization function is known, then the original histogram can be recuperated. The computation is not calculation intensive. A disadvantage of the strategy is that it is indiscriminate and extensive. It may increase and add to the contrast of background noise while lessening the usable signal.

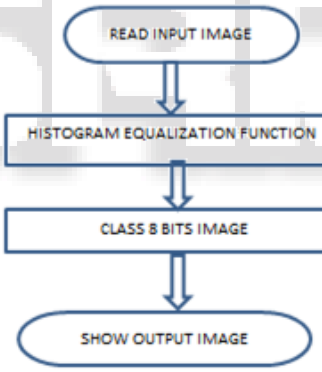

Fig. 7: Flowchart for histogram equalization

B. Contrast Stretching Algorithm

The rationale behind contrast stretching is to add the dynamic range of the gray levels in the image being processed.

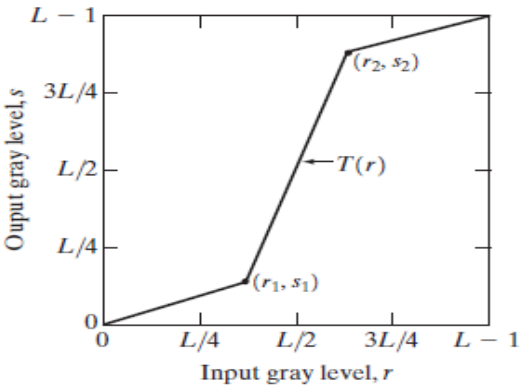

Fig. 8: Contrast Stretching Algorithm

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The depiction of points (r1, s1) and (r2, s2) commands the shape and state of the transformation function. The transformation is a linear function, whenever r1=s1 and r2=s2, that delivers no adjustments in gray levels. If r1=r2, s1=0 and s2=L-1, the transformation turns into a thresholding function that makes a binary image. Intermediate values of (r1, s1) and (r2, s2) generate different degrees of spread in the gray levels of the output image, subsequently influencing its contrast. In general, r1 ≤ r2 and s1 ≤ s2 is expected so that the function is single-valued and monotonically expanding. This condition protects the order of gray levels, subsequently avoiding the generation of intensity artifacts in the processed image.
The general form is

$$S = \frac{1}{1 + (m/r)^E}$$

Given s are the output image values, r are the input image values, m is the thresholding value and E is the slope.

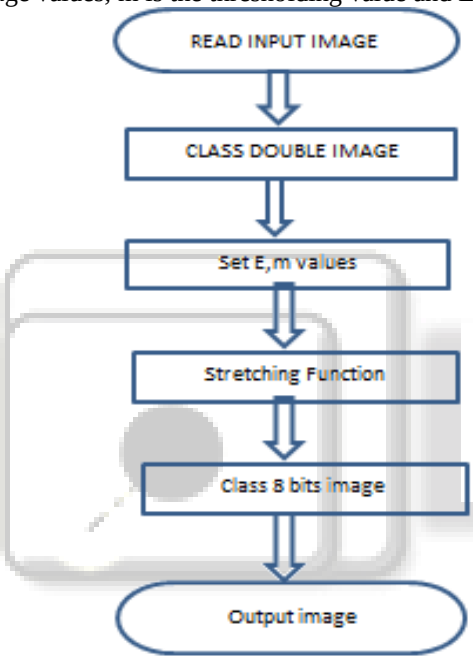


Fig. 9: Flowchart for contrast stretching algorithm

C. Local Enhancement Using Histogram Statistics

This technique is utilized to enhance elements over little areas in an image. The methodology is to characterize a square or rectangular neighborhood and shift the center of this area from pixel to pixel. At each location, the histogram of the points in the neighborhood is processed and either a histogram equalization or histogram specification transformation function is gotten. To map the gray level of the pixel centered in the neighborhood, this function is at long last utilized. The center or the focal point of the nearby region is then moved to an adjacent pixel location and the process is rehashed. As only one singular new row or column of the neighborhood alters during a pixel-to-pixel translation of the region, renewing the histogram attained in the previous location with the new data presented at each motion step is changes. We acknowledge two uses of the mean and variance for improvement purposes. The global mean and variance are determined over an entire image and are useful basically for gross adjustments of overall intensity and contrast. A considerably more powerful utilization of these two measures is in local enhancement, in which the local mean and variance are utilized as the premise for making improvements that rely on image characteristics in a predefined region for every pixel in the image.

$$m = \sum_{i=0}^{L-1} r_i * p(r_i)$$

$$\mu_2 = \sum_{i=0}^{L-1} (r_i - m)^2 * p(r_i)$$

Assume (x, y) be the coordinates for a pixel in an image, and then Sxy denotes a neighborhood (sub-image) of stated size, centered at (x, y).Given the equation below, the mean value mSxy of the pixels in Sxy can be found by

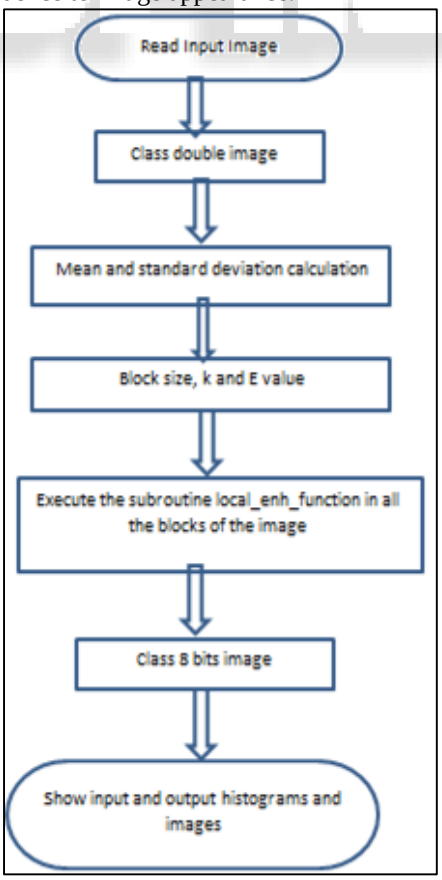
$$m_{S_{xy}} = \sum_{(s,t)\in S_{xy}} r_{s,t} * p\left(r_{(s,t)}\right)$$

rs, t is defined as the gray level at coordinates (s, t) in the neighborhood and pr (s, t) is the nearby normalized histogram component equivalent to that value of gray level.

Essentially, the gray-level variance of the pixels in region Sxy is defined by

$$\sigma^2{}_{S_{xy}} = \sum_{(s,t)\in S_{xy}} (r_{s,t} - m_{S_{xy}})^2 * p\left(r_{s,t}\right)$$

The local mean is a value signifying average gray level in neighborhood Sxy, and the variance (or standard deviation) is a count of contrast in that same area. A critical part of image processing utilizing the local mean and variance is the adjustability they allow in creating simple and straightforward, yet intense enhancement techniques in light of statistical measures that have a nearby, unsurprising correspondence to image appearance.



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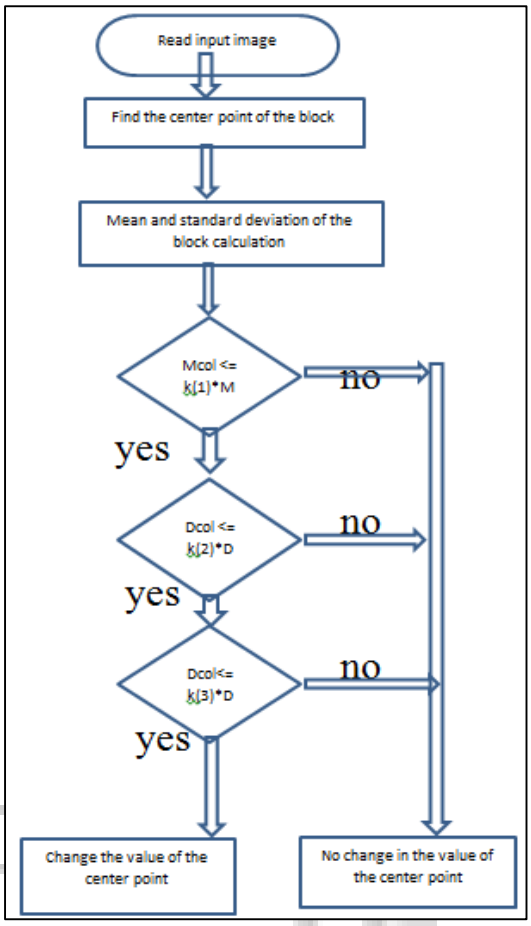

Fig. 10: Flowchart for Local enhancement technique

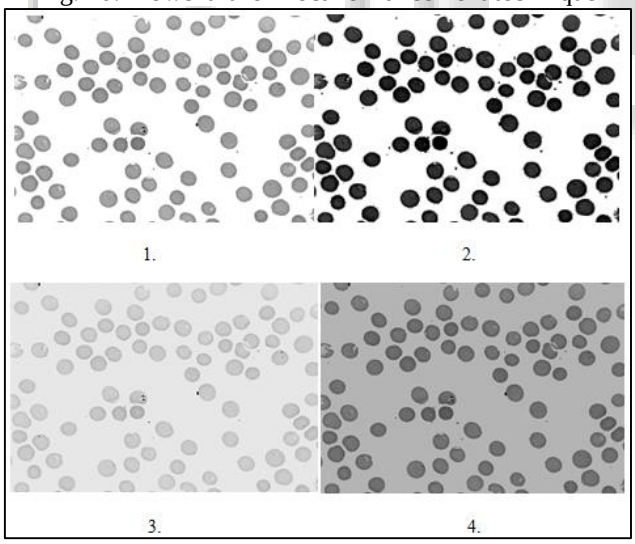

Fig. 11: Comparison of various contrast enhancement techniques. (1)Input (green channel of color normalized image), (2) Histogram Equalized, (3) Contrast stretched, (4) Local enhancement output

D. Color Deconvolution

To analyze the photometric and morphometric characteristics the, the relative contribution of dies must be isolated.

One of the major procedures used to deal with the issue of dissolution of the contribution of various stains is the utilization of color transformation techniques in light of the R-G-B (Red-Green-Blue) broadband data from any three channel cameras. In any case, one of the major detriments of the color transformation methods is that they do not bring about the separations of the contribution of two or more stains to the subsequent color. In histochemical and cytological staining generally, the areas are stained with more than one color, so extensive data is lost when above technique is utilized.

To conquer this issue and get a more precise result the color deconvolution method is created. This technique utilizes the broadband RGB data of the three channel camera. This strategy is efficient to the point that it can be utilized for separation of nearly all and every combination and mix of three or more colors, given that the colors are adequately dissimilar in their red, green or blue absorption features. These method origins on the orthonormal transformation of the original RGB image, relying on the user-driven color data of the three colors. After de-convolution, images can be remade independently and be utilized for densitometry and texture examination for each strain. This algorithm functions accurately when the background is neutral, so background subtraction and color correction must be enforced to image prior to handling.

After this, the de-convolution can be carried out utilizing the accompanying steps:-

Detect intensities of light transmitted and amount of stains with the absorbing factor, c, are portrayed by lamberts law as:

$$I_c = I_{0,c} \exp(-Ac_c)$$

The optical density (OD) is used for separation and for each channel it can be defined as:

$$OD_C = -log_{10}(I_C/I_{0,C}) = A * c_C$$

Each stain will be characterized by a specific OD for light and can be represented by a 3 X 1 OD vector. In the case of 3 channel color system it can be described as matrix of the form:

$$\begin{bmatrix} p11 & p12 & p13 \\ p21 & p22 & p23 \\ p31 & p32 & p33 \end{bmatrix}$$

To perform separation, we have to do the orthonormal transformation of the RGB information to obtain independent information about each strain's contribution. The transformation has to be normalized to achieve correct balancing of the normalization factor. To implement normalization every OD vector is divided by its complete length:

$$\hat{p}_{11} = p_{11}/\sqrt{{p_{11}}^2 + {p_{12}}^2 + {p_{13}}^2}$$
$$\hat{p}_{21} = p_{21}/\sqrt{{p_{21}}^2 + {p_{22}}^2 + {p_{23}}^2}$$
$$\hat{p}_{31} = p_{31}/\sqrt{{p_{31}}^2 + {p_{32}}^2 + {p_{33}}^2}$$

In this way, culminating in a normalized OD matrix:

$$\begin{bmatrix} \hat{p}11 & \hat{p}12 & \hat{p}13 \\ \hat{p}21 & \hat{p}22 & \hat{p}23 \\ \hat{p}31 & \hat{p}32 & \hat{p}33 \end{bmatrix}$$

If C is the 3 X 1 vectors for the amounts of the three strains at a particular pixel, then the vectors of OD level detected at that pixel is:

$$Y=CM$$

We can imply that, if we multiply the OD image with the inverse of the OD matrix, known as color-deconvolution matrix, D, results in orthogonal representation of the strains forming the image:

$$C=D[Y]$$

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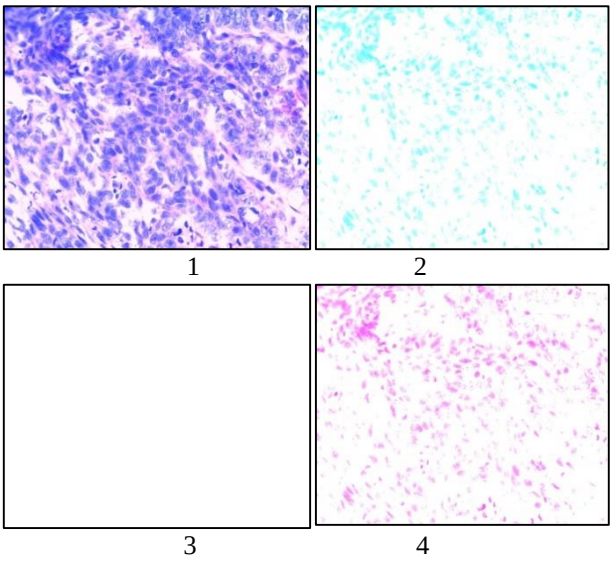

Fig. 12: Performance of Color Deconvolution ((1) Input image, (2) Contribution of DAB, (3) Contribution of Haemotoxylin, (4) Contribution of Eosin)

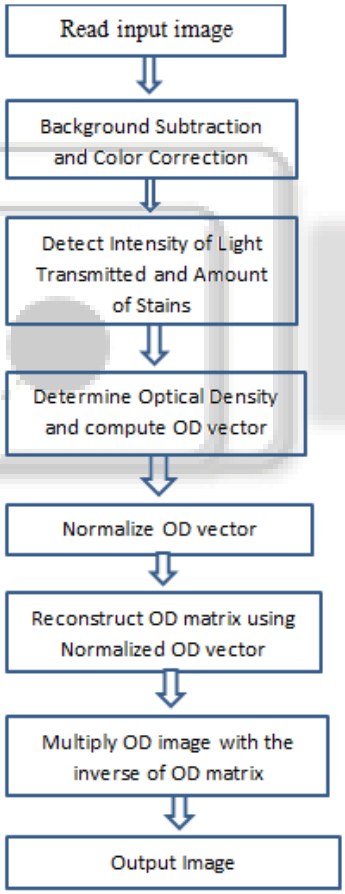

Fig. 13: Flowchart for Color Deconvolution

IV. CONCLUSION

From the output images, it can be concluded that quadratic mapping of intensities provides good results for color normalization. But if we have to focus on the objects rather than the background, it is better to use diagonal matrix approach as it provides good results for all the images. For contrast enhancement, contrast stretching algorithm gives good results when applied to the green channel of color corrected RGB images. Color Deconvolution is the only efficient method to separate the contributions of more than one stain in a multistained histochemical image.

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