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RETINEX IMAGE PROCESSING: IMPROVING THE VISUAL REALISM OF COLOR IMAGES

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Sensations of color show a strong correlation with reflectance, even though the amount of visible light reaching the eye depends on the product of reflectance and illumination. The visual system must achieve this remarkable result by a scheme that does not measure flux. Such a scheme is described as the basis of Retinex theory. This paper deals with image enhancement techniques basically Retinex and its constituents, namely Small Scale Retinex (SSR), Multi Scale Retinex (MSR) and Multi Scale Retinex with Color Restoration (MSRCR). The techniques enable color rendition and dynamic range compression in case of 'dark' or 'low lit' images. The Multi Scale Retinex (MSR) is a generalization of the SSR, which, in turn, is based upon the last version of Land's center/surround retinex. The current version, the multi scale Retinex with color restoration (MSRCR), combines the dynamic range compression and color constancy of the MSR with a color 'restoration' filter that provides excellent color rendition. The MSRCR has been tested on a very large suite of images. We provide a general overview of the types of operations that can be performed on the image in order to enhance its quality.

1. Introduction

Image Enhancement improves the quality (clarity) of images for human viewing. Our paper deals with a few techniques based on Retinex theory contributing to the enhancement of an image especially dark or low-lit images. The Retinex Image Enhancement Algorithm is an automatic image enhancement method that enhances a digital image in terms of dynamic range compression, color independence from the spectral distribution of the scene illuminant, and color/lightness rendition. The digital image enhanced by the Retinex Image Enhancement Algorithm is much closer to the scene perceived by the human visual system, under all kinds and levels of lighting variations, than the digital image enhanced by any other method. The comparison of this technique with other image enhancement techniques has been studied and codes for homomorphic filtering are developed. The result section contains comparison of original image, SSR image, MSR image, MSRCR image and the output of homomorphic filtering. Finally it is concluded that output of MSRCR is better than other techniques.

2. Retinex Theory

A human observer can easily see individual objects both in the sunlight and shadowed areas, since the eye locally adapts while scanning the different regions of the scene. When attempting to display the image on a display, either the low intensity areas are underexposed and look black or the high intensity areas are overexposed and cannot be seen.

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Images taken from digital cameras suffer from a loss in clarity of details and color as it depends on the illuminance which in term varies with distance from source. This problem of Color Constancy in images is solved using the basis of Retinex Theory.

A. Retinex Image Enhancement

The Retinex takes an input digital image I and produces an output image R on a pixel by pixel basis as in the following equation (1):

$$R(x, y) = \frac{\log(I(x, y)}{\log(I(x, y) * M(x, y)} \tag{1}$$

where $M(x, y) = \exp(x^2 + y^2)/\sigma^2)$ is a constant which controls the extent of M, and σ represent spatial convolutions.

B. Reflectance–Illuminance

The input image can be written as the product of two components: $\sigma(x, y)$ the reflectance component which represents the light reflected from all the objects in the scene being imaged, and i(x, y) which represents the illumination component as in equation (2):

$$I(x, y) = i(x, y)\, \rho(x, y) \tag{2}$$

- Since the illumination component varies very slowly across the scene in equation (3) and (4),

$$I(x, y) = I_0\, \rho(x, y) \tag{3}$$

And $$R(x, y) = \log (I_0\rho(x, y) / I_0\, \rho(x, y) * M(x, y) \tag{4}$$

- By performing the same operation on each color channel, the output color image can be written as equation (5).

$$R(x, y) = \log (I_1 (x, y)/ I_1 (x, y)* M(x, y))...ie\{R, G, B\} \quad (5)$$

$R_i(x, y)$ is dependent upon the size of the surround mask which is parameterized by σ.

- Different values of σ enhance different features of the input image, equation (6).

$$R_i (x, y) = 1/k \left(\sum_{k=0}^{k} \left(\log \left(\frac{I_i (x, y)}{I_i (x, y) * M(x, y)} \right)\right)\right) \quad (6)$$

C. Image Formation

Based on the image formation mode shows equation (7):

$$S(x, y) = L(x, y) R(x, y) \quad (7)$$

An image S is the pixel-by-pixel product of the ambient illumination L and the scene reflectance R. The Retinex algorithm deals with the problem of separating the two quantities: first estimating the illumination information and then obtaining the reflectance by division. Working in a logarithmic domain, the above relation can be expressed as-Figure1.

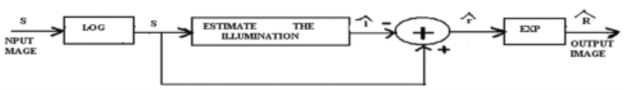

Fig. 1: Basic of Retinex Algorithm

D. Categories of Retinex Algorithms

- Set of path-based algorithms where the new pixel value depends on the multiplication of ratios along the path.
- Recursive comparison of new pixel with surrounding pixels.
- Centre/surround Retinex where the new pixel value depends on the comparison of a given pixel and the surrounding average pixel values.
- Mathematical formulas which converts the constraints of illumination and reflectance into mathematical problem and then obtains the new pixel values.

E. Development of Retinex Techniques

- Single Scale Retinex (SSR)
- Multi-Scale Retinex (MSR)
- Multi-Scale Retinex with Color Restoration (MSRCR)
- Multi-Scale Retinex with canonical gain/offset

3. SINGLE SCALE RETINEX

Jobson and his co-worker defined a single-scale Retinex (SSR), which is an implementation of center/surround Retinex. The Single-scale retinex is given by equation (8).

$$R_i(x, y) = \log I_i(x, y) - \log [F(x, y) * I_i(x, y)] \quad (8)$$

Where $R_i (x, y)$ is the retinex output, $I_i (x, y)$ is image distribution in the i^{th} color band,''*'' denotes the convolution operation is the normalized Gaussian function given by equation (10).

$$F(x, y) = ke^{-(x2 + y2)c2} \quad (10)$$

c is the Gaussian surround space constant, or the scale and is selected such that, equation (11).

$$\iint F(x, y)dxdy = 1 \quad (11)$$

The image distribution is the product of scenes reflectance and illumination given by equation (12)

$$I_i (x, y) = S_i(x, y)\, r_i(x, y) \quad (12)$$

Where $S_i(x, y)$ is the spatial distribution of illumination and the distribution of scene reflectance. The convolution with surround function works as averaging in the neighborhood. Generally the illumination has slow spatial variation, which means equations (13-a, 13-b, 13-c).

$$R_i(x, y) = \log \{(Si (x, y)\, r_i (x, y)/ \sqrt{S_i (x, y) r_i (x, y)}\} \quad (13\text{-a})$$

$$S_i (x, y) \approx \sqrt{S_i (x, y)} \quad (13\text{-b})$$

$$R_i (x, y) \approx \log \{r_i (x, y)/ \sqrt{r_i (x, y)}\} \quad (13\text{-c})$$

Hence the illuminance term can be eliminated from the retinex obtained making color constancy possible.

A. Characteristics of SSR

SSR has been defined to have the following characteristics and properties-

- The functional form of the surround is a Gaussian.
- The placement of the log function is after surround formation.
- The post retinex signal processing is a canonical gain offset rather than an automatic gain offset.
- There is a trade off between dynamic range compression and tonal rendition which is governed by the Gaussian surround space constant. A space constant of 80 pixel is a reasonable compromise between dynamic range compression and rendition.
- A single scale seems incapable of simultaneously providing sufficient dynamic range compression and tonal rendition.
- Violations of the gray world assumptions has led to retinex images which were either greyed out locally or globally or more rarely suffered from colour distortion.

4. Multiscale Retinex

Recent work advocates MSR as a method to bridge the gap between what a camera sees and what a human sees, with the goal being to provide image reproductions which are very similar to what the human viewer would have seen, were they present when the picture was taken.

We believe that the chief conceptual problem using MSR in this way is that a number of image-processing tasks are performed simultaneously without sufficient regard to the interactions occurring between them.

The main practical consequence of this is that MSR is not appropriate for applications which are sensitive to color. In the image processing/image enhancement context, MSR serves a subset of the following four image processing goals, depending on the circumstances:

(i) Compensating for uncalibrated devices (gamma correction)

(ii) Color constancy processing

(iii) Dynamic range compression

(iv) Color enhancement

Because of the tradeoff between dynamic range compression and color rendition, we have to choose a good scale c in the formula of F(X, Y) in SSR. If we do not want to sacrifice either dynamic range compression or color rendition, multi-scale retinex, which is a combination of weighted different scale of SSR, is a good solution, given by equation (14) and (15).

$$R_{MSRi} = \sum_{n=1}^{N} w_n R_{ni} \tag{14}$$

$$R_{MSRi} = \sum_{n=1}^{N} w_n \{\log I_i(x,y) - \log[F_n(x,y) * I_i(x,y)]\} \tag{15}$$

Where N is the number of the scales, R_{ni} is the i^{th} component of the n^{th} scale. The obvious question about MSR is the number of scales needed, scale values, and weight values. Experiments showed that three scales are enough for most of the images, and the weights can be equal. Generally fixed scales of 15, 80 and 250 can be used, or scales of fixed portion of image size can be used. The MSR output is different from existing techniques in that the overall effect of processing is scene dependent but the processing itself is not. In other words, though the overall effect adapts itself to lighting variations within the scene process, with exactly the same control parameters can be used for any image. This is not true for other adaptive techniques since variations in lighting conditions imply variations in the control parameters.

5. MSR to MSRCR

A. MSR Style Algorithms and Color Fidelity:

Color fidelity in image reproduction is a complex and active research topic. First we assume that changing the intensity does not change the perceived non-intensity aspects of color. This assumption is, of course, only an approximation. Even for isolated colors, color appearance does change with intensity.

We also note that the original MSR also does not address these problems, and that our modified version of MSR is the MSRCR is more suited to adding corrections for deviations from the above assumption. We thus acknowledge that an important area for future work is to include more complex color appearance models, including ones for simultaneous contrast as already discussed.

For the purposes of this work, then, we assume that a first approximation of faithful color reproduction is to preserve chromaticity, as defined by equation (16).

$$X = \frac{X}{X+Y+Z} \text{ and}$$

$$Y = \frac{Y}{X+Y+Z} \tag{16}$$

If we assume that the region's reproduced chromaticity X', Y' matches the region's scene chromaticity XY, then it follows immediately that, equation (17).

$$X' = KX,\ Y' = KY,\ Z' = KZ \tag{17}$$

where $$K = \frac{X' + Y' + Z'}{X+Y+Z}$$

Similarly, scaling the reproduction X', Y', Z' by a constant k preserves chromaticity. Thus to preserve chromaticity we can manipulate k on a region-by-region basis, but not otherwise. Normally we deal with intermediate variables such as camera RGB. In order to be confident that a good approximation of scene chromaticity is being reproduced, we need to know the relationship between the input scene and, XYZ and RGB, the reproduction X', Y', Z'. If we know these relationships, then we can map intermediate variables into ones which are linearly related to XYZ input and output $X' Y' Z'$. Having done so, we can manipulate the reproduced contrast while preserving chromaticity by scaling pixel RGB. Linearity from RGB to X' Y' Z' ensures that the chromaticity reproduced by (kR, kG, kB) is the same as that reproduced by (R, G, B). Applying gamma correction to the result of MSR processing normally gives poor results. Specifically the images look washed out and over gamma corrected. The problem with just accepting and using this coincidence as a conveniently provided gamma correction is that device calibration (gamma correction) is meant to compensate for devices, but now one is committed to a single method, and thus the result is device dependent. Regardless, since MSR can, to some extent, play the role of gamma correction, it is important to ensure proper gamma correction is being applied to the original image when being compared to MSR results on a monitor. Based on visual inspection, and the chromaticity results presented below, we suggest that MSR effectively applies a gamma correction in the range of 2 to 2.5, which we will refer to as the MSR equivalent gamma.

B. Color Restoration

The general effect of retinex processing on the images with a regional or global gray world violation is a graying out of the image either in specific regions or globally. More rarely the gray world violations can simply produce an unexpected color distortion. In this paper, we extend a previously designed single scale centre/surround retinex to a multi-scale version that achieves simultaneous dynamic range compression/color consistency/lightness rendition.

C. Chromaticity Preserving MSR

We now outline the approach to MSRCR. As mentioned earlier, the main idea is to separate the processing goals of MSR so that each one can be done more optimally. First we ensure that the input is linear. Then we optionally apply color constancy processing to correct for mismatches between the imaging system and the illumination. This is followed by MSR style processing on an appropriately defined image luminance. The RGB of the output image pixels are then set so that their chromaticity is the same as in the original linear image, but their luminance are the result of the previous processing step.

D. Gain-offset Adjustment, Color Enhancement and Output

The next step is to apply the offset part of the offset-gain algorithm. Here the range of the luminance result is offset so that some of the dark pixels are clipped at zero. If color enhancement is desired, then it is best added at this stage. The chromaticity of the pixels that are clipped will be a slightly incorrect, but this is not normally noticeable. It is not recommended, however, to do the same with the bottom of the range, as this can affect the chromaticity of all the pixels. Instead it is generally better to increase the amount of clipping on the bottom by doing so when the luminance range is adjusted, as described above.

6. MULTISCALE RETINEX WITH COIOR RESTORATION ALGORITHM

The current version, the multi scale retinex with color restoration (MSRCR), combines the dynamic range compression and color constancy of the MSR with a color 'restoration' filter that provides excellent color rendition. The MSRCR has been tested on a very large suite of images. The general form of the MSRCR can be summarized by the following equation (18):

$$R_{Mi}(x, y) = G_r F_i(x, y) \sum_{n=1}^{N} w_s (\log[\mathbf{I}_i(x, y)] - \log[I_i(x, y) * M_s(x, y)]) - O_r \qquad (18)$$

Where i =1 to N, Where R_{mi} is the i^{th} band of the MSRCR output, s is the number of scales being used, w_s is the weight of the scale, I_i is the i^{th} band of the input image, and B is the number of bands in the input images. The surround function M_s is defined by equation (19).

$$M_s(x, y) = K \exp \frac{\rho_s^2}{x^2 + y^2} \qquad (19)$$

where ρ_s is the standard deviation of the s^{th} surround function, and

$$\iint K \exp \frac{\rho_s^2}{x^2 + y^2} \, dx \, dy = 1$$

$F_i(x, y)$ is the color restoration functions defined by equation (20).

$$F_i(x, y) = G_f \log[I_i(x, y) / (\textstyle\sum_{n=1}^{N} 1_n(x, y)) - O_f] \qquad (20)$$

G_f and O_f: are, respectively, the final gain and offset values needed to scale the output of the log domain operations to the (R, G, B) color space, and G_f and O_f and control the degree to which the color restoration function F(x, y) affects the overallcolor of the output image. These constants, the number of scales S and the widths of the surround functions, are image independent in the sense that we apply the same (canonical) set of constants to every image that we process. The color restoration can also be calculated using the expression given by equation (21).

$$C_i(x, y) = \beta\{\log[\alpha I_i(x, y)] - \log[\Sigma I_i(x, y)]\} \qquad (21)$$

where β – Gain Constant and α – Controls the strength of nonlinearity. The final representation of MSRCR is represented as equation (22):

$$R_{MSRCRi}(x, y) = G[C_i(x, y) * R_{MSRi}(x, y) + b \qquad (22)$$

Where, G – Gain Constant, b – Gain Offset value;

G – Final Gain – 192;, b – Offset Value – 30;

α – Strength of non-linearity – 125;

β – Control gain constant - 46

Although these constants are not optimal for most images, they yield serviceable results for many images, and thus we agree that widespread applicability of the constants is strength of MSRCR.

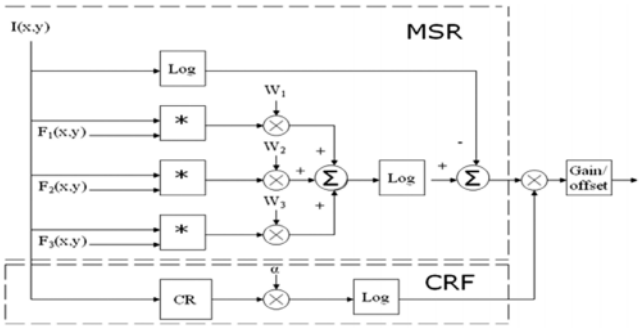

Fig.2: Block Diagram of MSRCR

As a start, we have experimented with some input dependent methods for the gain offset adjustment, where heuristics are applied to the image histogram to find gain offset parameters. The block diagram of MSRCR is shown above as fig.2.

7. Comparison With Other Techniques

A. Non-linear Gamma Correction

Good visual representations seem to be based upon some combination of high regional visual lightness and contrast. To compute the regional parameters, we divide the image into non overlapping blocks that are 50×50 pixels. For each block, a mean, I, and a standard deviation, σ_f, are computed. A first approach was to postulate that for visually good rendition the contrast & lightness product should be above a minimum value, with the additional constraint that each component cannot fall below an absolute minimum value.

This regional scale is sufficiently granular to capture the visual sense of regional contrast. Both the contrast and the lightness can be measured in terms of the regional parameters.

The coupling of the constraints of minimum contrast-lightness product with minimum contrast and lightness as separate entities defines the zone in figure labeled “visual good”. Further, this figure suggests that there may exist a contour of much higher contrast-lightness, which can be considered a “visual ideal”.

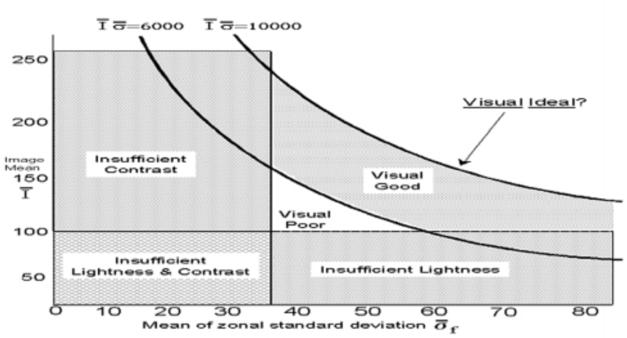

Fig.3 : Variation of Image Intensity and Contrast

When images are displayed on monitors, their intensity profile is typically modified using the gamma-transformation given by equation (23): (23)

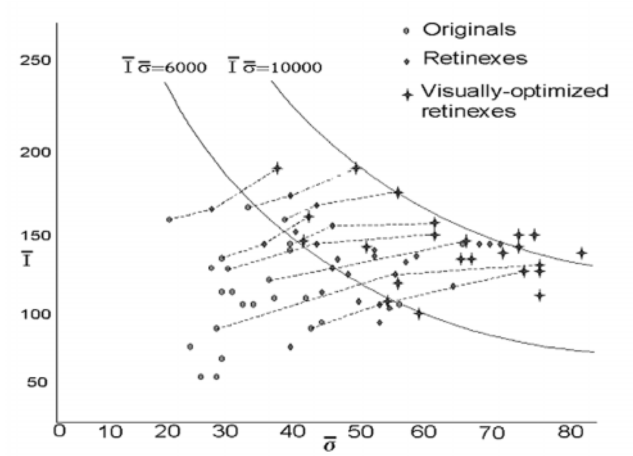

Fig.4: Comparison Between Original and Retinex Image

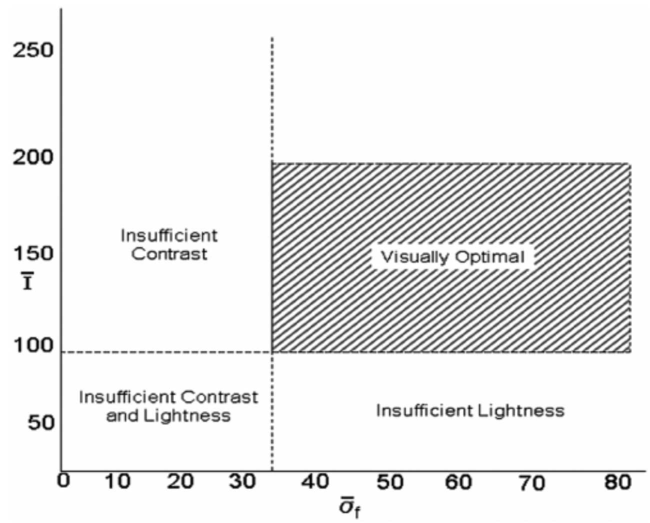

Fig.5: Showing Visually Optimal Area

Where, $I_i(x, y)$ is the input value, and $I_0(X, Y)$ is the modified value. A value of γ^{-1} is the linear transform. In order to gauge our results against a linear baseline for the original image data, we determined that most digital images are super-linear and should be corrected to approximate linearity by gamma transforming the processed image using $\gamma = 0.63$. While this has negligible effect on standard deviation values, it just adjusts the mean downward from about 165 to about 128. as shown in figure in (3) (4) & (5).

B. Histogram Equalization

A global technique that works well for a wide variety of images is histogram equalization. This technique is based on the idea of remapping the histogram of the scene to a histogram that has a near-uniform probability density function. This results in reassigning dark regions to brighter values and bright regions to darker values.

C. Homomorphic Filtering

The technique that most resembles retinex algorithm, conceptually and functionally, is homomorphic filtering. Homomorphic filter is used for image enhancement. It simultaneously normalizes the brightness across an image and increases contrast. Here homomorphic filtering is used to remove multiplicative noise. The high-pass filtering is used to suppress low frequencies and amplify high frequencies, in the log-intensity domain. Mathematically, it cab be represented as shown in equation (24 to 28)

$$S_i(x, y) = \ln[I_i(x, y)] \quad (24)$$

$$S_i'(v, w) = F[S_i(x, y)] \quad (25)$$

$$S_i''(v, w) = S_i'(v, w)H(v, w) \quad (26)$$

$$S_i'''(x, y) = F^{-1}[S_i''(v, w)] \quad (27)$$

$$I_i'(x, y) = \exp[S_i'''(x, y)] \quad (28)$$

Where F[] and F^{-1}[] represent the Fourier and inverse Fourier transforms respectively. H represents the homomorphic filter. It is in its final exponential transform that the homomorphic filter differs the most from the MSRCR. MSRCR does not apply a final inverse transform to go back to the original domain.

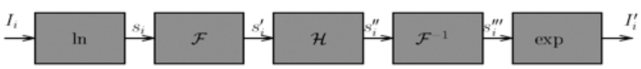

Fig.6: Block Diagram for Homomorphic Filtering

The homomorphic filter consistently provided excellent dynamic range compression but is lacking in final color rendition. The output of the homomorphic filter in effect appears extremely hazy compared with the output of the MSRCR though the dynamic range compression of the two methods appears to be comparable as shown in figure (7).

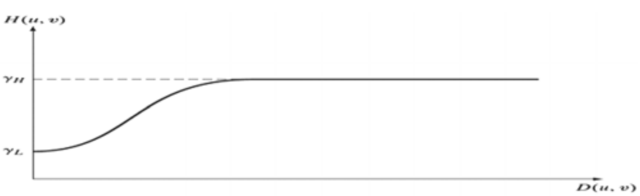

Fig.7: Characteristics of Homomorphic Filter Used

D. Manual Image Enhancement

We have provided a brief description of the commonly encountered "problems" introduced inevitably in a digital image due to the nature of the acquisition process and the pre-processing algorithms. The MSRCR has proven to be quite resilient to many of the arbitrary operations that are used in digital image formation and can thus be truly considered a fully automatic process.

8. Conclusion And Results

The SSR provides a good mechanism for enhancing certain aspects of images and providing dynamic range compression. However it is limited in its use because it can either provide good tonal rendition or dynamic range compression. The MSR comprises of 3 scales-small, intermediate and large- overcomes this limitation and is found to synthesize-dynamic range compression, color constancy, tonal rendition and produce results which compare favorably with human visual perception except for the scenes which contain violations of the gray world assumption. As compared with other image enhancement techniques, the Retinex enhancement has the following advantage:

- Image enhancement is a process independent of inputs;
- Has general application on all pictures.
- Good dynamic range compression and color rendition effect.

MSRCR provides proportional RGB components in color images which is an improvement over MSR technique which is preferred for gray images. Optimized scale, gain and offset parameters have been investigated and analyzed for better results. We have provided a brief description of the most commonly used image enhancement techniques and compared their operation with the multiscale retinex with color restoration. Application to various fields has been shown (8) & (9).

Fig.8 (a) Original Image (b) SSR Image (c) MSR Image (d) MSRCR Image (e) Homomorphic Filtering

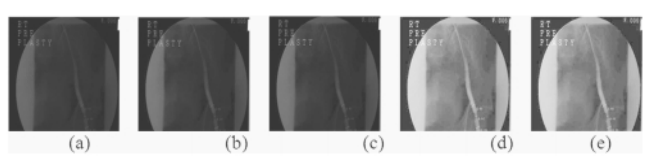

Fig.9: X – Ray Image (a) Original Image (b) SSR Image (c) MSR Image (d) MSRCR Image (e) Homomorphic Filtering

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