A Comfortable Imaging on Display

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Abstract
Most of past image processing systems have been designed independent of image contents. Now, evolving computation power is making the "*image-dependent*" elegant algorithms possible to get the better image renditions on display. This paper introduces our recent approaches to quality and pleasant imaging based on *image-dependent*. Three typical approaches to comfortable "*Sharpness*", "*Lightness*", and "*Color*" renditions on display image are presented.

1. Introduction
Seeing 600th anniversary of Gutenberg's birth in 2000 A.D., we should look back the historical significance of letterpress technology and take a step forward into digital imaging new age. Now imaging technology plays a leading role in visual communication, but meets severe assessment to satisfy human vision. Not only high precision and high definition digital media, but also "*intelligent image processing*" will be necessary for more aesthetic and pleasant imaging. Collaboration with vision research and development in content-based algorithm are expected to advance the next generation color imaging for multi-media.
This paper introduces our recent approaches to a pleasant imaging based on the concept of *image-dependent*.
This paper introduces the following three applications

[1] Adaptive Edge Sharpening with smoothing
[2] Adaptive Scale-Gain Retinex Model
[3] Image-dependent Gamut Expansion:

Fig.1 shows a part of intelligent image processing system developed in our laboratory.

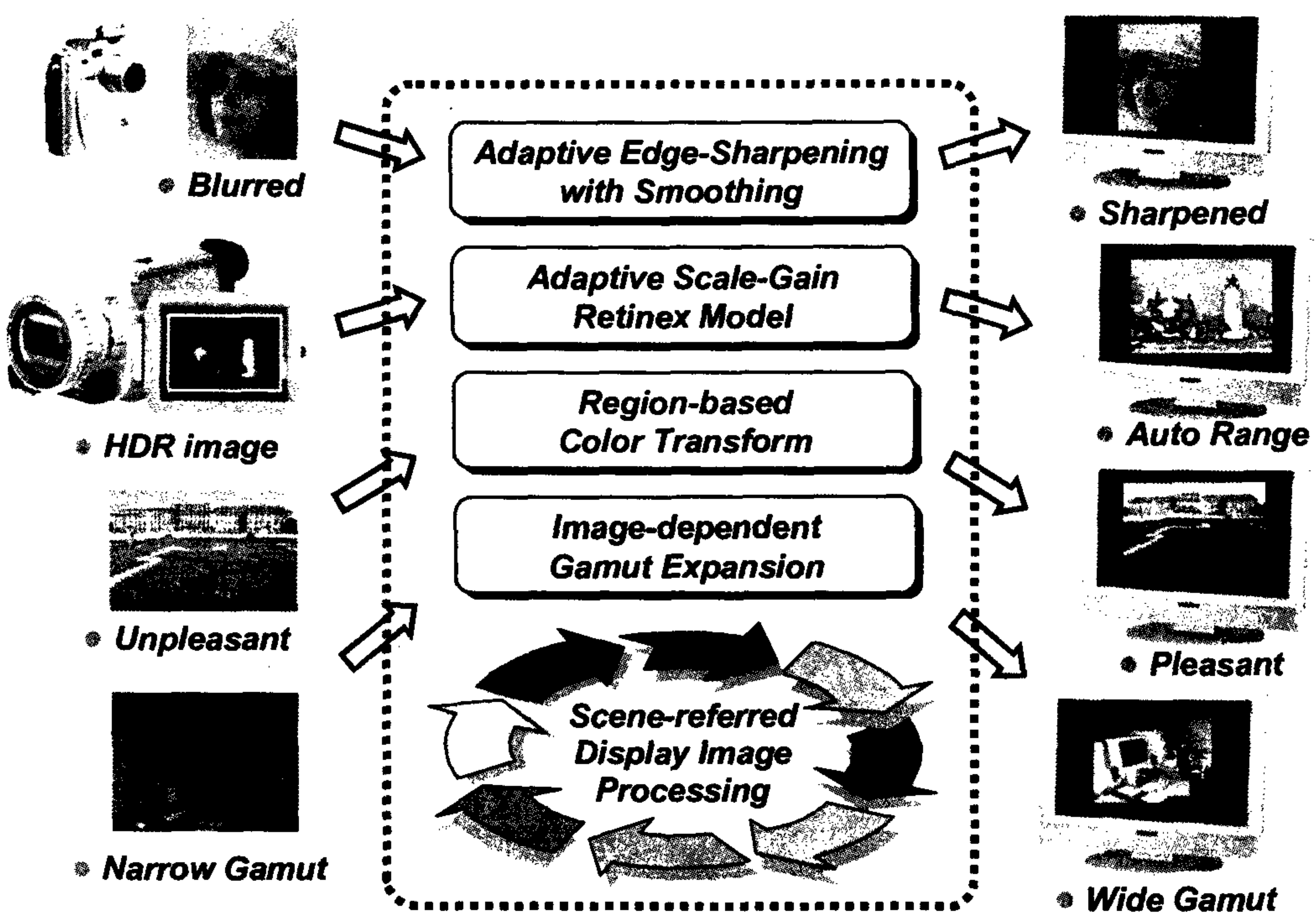

Fig.1 Image Processing System for displaying comfortable color images

2. Adaptive Image Sharpening
Image blurring mechanism is modeled analogous to a diffusion process in physical phenomena and image sharpening process is described as its inverse diffusion. So far, a great variety of image sharpening algorithms for backward diffusion has been developed. Linear unsharp masking (*USM*) method or Laplacian filter are most widely used for image sharpening.
In practice, the ***USM*** or ***Laplacian*** operators are given by second order derivatives and realized by local spatial filters. Although these image sharpening filters are simple and work well in many applications, they have two main drawbacks: (1) Linear operator makes a system very sensitive to noise resulting in unpleasant granularity. (2) It enhances high-contrast areas much more with unpleasant overshoot artifacts. Various approaches have been done for reduce the noise sensitivity based on the use of nonlinear operators as follows.

Adaptive USM (A-USM) model by Polesell: designed to work sensitive to detail areas with medium contrast and insensitive to the uniform areas. A cost function is defined by a measure of local dynamics

- ***Cubic USM (C-USM) model*** by Ramponi: introduced a quadratic function to be sensitive to high-gradient but less sensitive to slow gradient edge areas.
- ***Rational USM (R-USM) model*** by Ramponi: extended ***C-USM*** by adding the rational control term to enhance the edges higher in detail zone and lower in relatively uniform zone depending on the local variances.
- ***Wavelet USM (W-USM)*** model by Okazaki: improved ***C-USM*** by Multi-Scale gradients of Wavelet.

While a variety of vision-based edge detection operators have been considered such as Gaussian Derivative (***GD***), ***Gabor***, ***DOG***, ***DOOG***, or ***DODOG***. Young[4] and others reported ***GD*** is the best to minimize the joint space-spatial frequency uncertainty $\Delta x \bullet \Delta \omega$. We have also applied vision-based ***Multi-Scale GD(MGD)*** operators. The basic Gaussian distribution function and its second derivative are defined by

$$G(r) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{r^2}{2\sigma^2}\right);\ r^2 = x^2 + y^2$$

$$\nabla^2 G = \frac{1}{\pi\sigma^4}\left(\frac{r^2}{2\sigma^2} - 1\right) exp\left(-\frac{r^2}{2\sigma^2}\right) \qquad (1)$$

The edge signals are extracted from input image g(x, y) by the two-dimensional convolution operation by

$$\delta(x,y) = -\nabla^2 G(x,y) * g(x,y) \qquad (2)$$

The edge types are classified by measuring the edge strength through a pre-scanning GD filter ($-\nabla$2GS) with appropriate standard deviation σ_S. Fig.2 illustrates the sharpening process in our system. New model has both functions of sharpening and smoothing. A pre-scanning filter classifies the edge types into *hard*, *medium*, *soft*, and separates the *flat* areas. Three different ***GD*** filters are selectively applied to the classified edge types and a normal Gaussian filter is used for *flat* area noise reduction.

First, the performance of our system was compared with that of existing nonlinear ***USM models*** for monochrome image. Fig3 shows a result for *Lena images. Lena1* is a normally blurred sample with

small background noise but *Lena2* is heavily degraded by blurring and Gaussian noise. Among them, our model worked best especially in the noise reduction in the flat areas by intentionally applied smoothing filter.

Fig.4 shows a sharpened sample applied to color image. In comparison with conventional method, the proposed model sharpened the edge slopes naturally and reduced the background noises dramatically

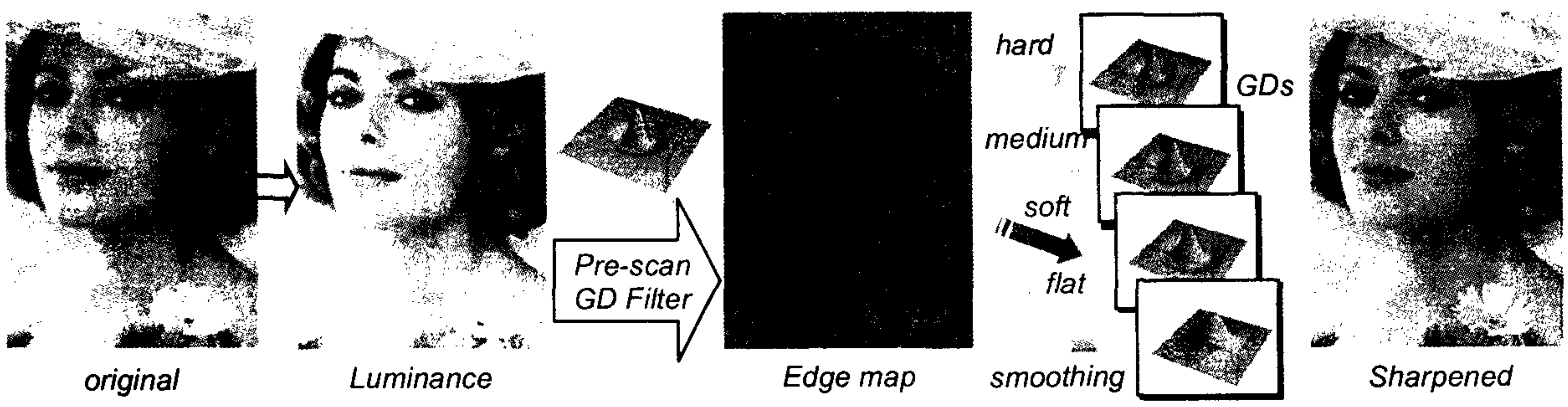

Fig.2 Overview of adaptive image sharpening method with multiple GD filters

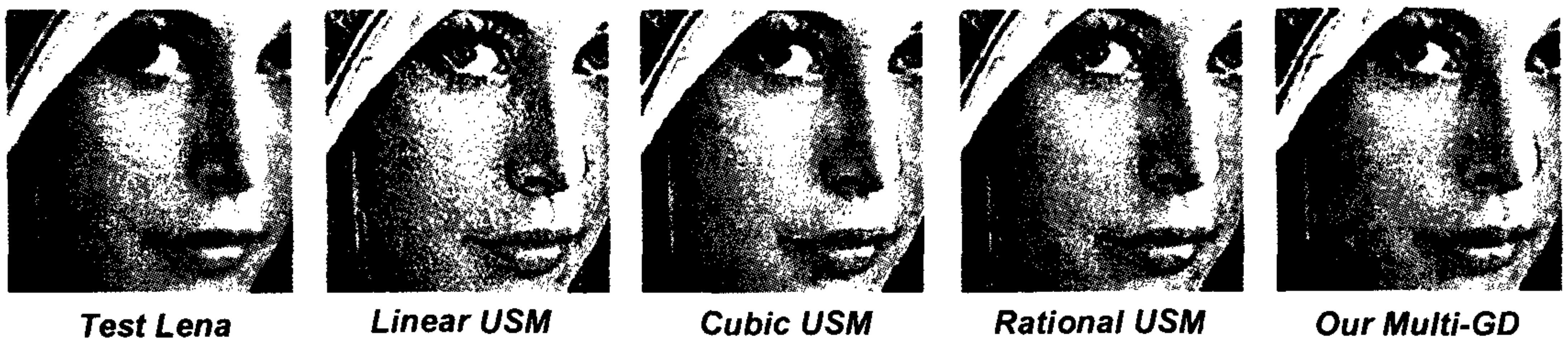

Fig.3 Comparison in sharpened monochrome image by adaptive multi-GD filters vs. existing nonlinear USMs

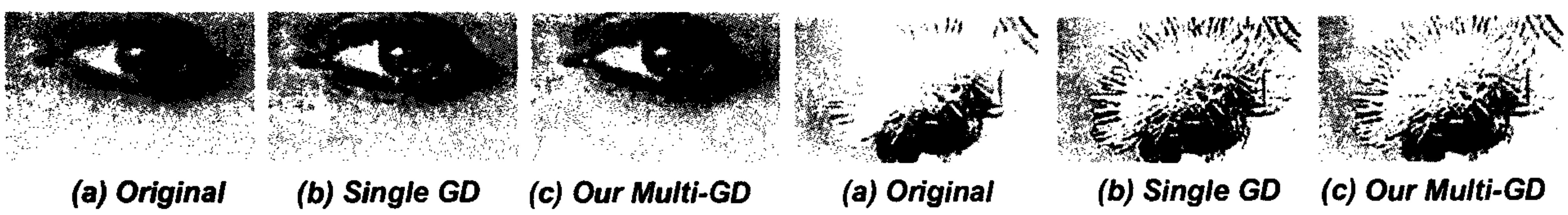

Fig.4 Noise reduction effect in adaptive multi-GD filters for color image

3. Adaptive Scale-Gain Retinex

The second topic is addressed to image-dependent Lightness control. Human vision can perceive 104 order of luminance range by adaptation mechanism. But the picture taken by electronic camera under the heavy change in highlight and shadow often looks different because of lack of ranges. Retinex model proposed by Land and McCann controls the scene lightness automatically. Jobson et al, NASA advanced the single-scale retinex (SSR) into multi-scale retinex (MSR) based on the center/ surround (C/S) model.

Letting the camera image $I(x, y)$ be a product of light source $L(x, y)$ and scene reflectivity $R(x, y)$ given by $I(x, y) = L(x, y) \bullet R(x, y)$, scene reflectivity is simply recovered by taking the C/S ratio

$$\hat{R}(x,y) \cong I(x,y)/\hat{L}(x,y) = I(x,y)/\bar{I}(x,y) = \textit{Center luminance/Surround luminance} \quad (3)$$

In the basic SSR, surround S is calculated by convolving the input image with Gaussian filter.

Since the C/S ratio rises up higher or goes down lower according to the surround is darker or lighter, the center pixel gain is automatically adjusted and the shadow areas become visible. Fig. 4 shows the principle of Retinex.

MSR presents improved output by the weighting sum of plural SSRs. However the decision rule of weights is not clear but empirical. We developed scene-adaptive MSR model which determines the weights automatically dependent of image content. In our Adaptive MSR, the Retinex output Ri(x. y. □m) for i=R. G. B is calculated as follows

$$R_i(x,y,\sigma_m) = \frac{C}{M}\sum_{m=1}^{M} A(\sigma_m)\left\{\frac{I_i(x,y)}{S_m(x,y,\sigma_m)}\right\}$$
$$i = R,G,B,\ \ \sigma_m = 2^m,\ \ m = 1,2,\Lambda,M \quad (4)$$

$$S_m(x,y,\sigma_m) = \langle G_m(x,y) \otimes Y(x,y) \rangle$$
$$G_m = K\exp[-(x^2+y^2)/\sigma_m^2] \quad (5)$$

Image-dependent scale-gain function $A(\sigma_m)$ is given as follows.

$$A(\sigma_m) = M\left\{\Sigma_{C/S}(\sigma_m) / \sum_{m=1}^{M}\Sigma_{C/S}(\sigma_m)\right\}$$
$$\Sigma_{C/S}(\sigma_m) = \text{standard deviation in } \textbf{\textit{SSR}} \text{ Histogram} \quad (6)$$

The model parameters in the conventional Retinex represented by NASA have been empirically optimized and complicated. In our model, a scale-gain function $A(\sigma_m)$ is automatically determined based on statistics and depending on image contents.

Fig.6 shows a comparison of MSR images. All the Retinex images are dramatically improved in shadow visibilities. The proposed scene-adaptive MSR is best in color appearance, while NASA is best in resolution. In most cases, we don't know what image is ideal, unless we see the original scene through our eye at the same place and at the same time. Although our model worked in robust for many natural images, an ideal test target is necessary for the best optimization of parameters. A method for synthesizing the test target image on screen is under development.

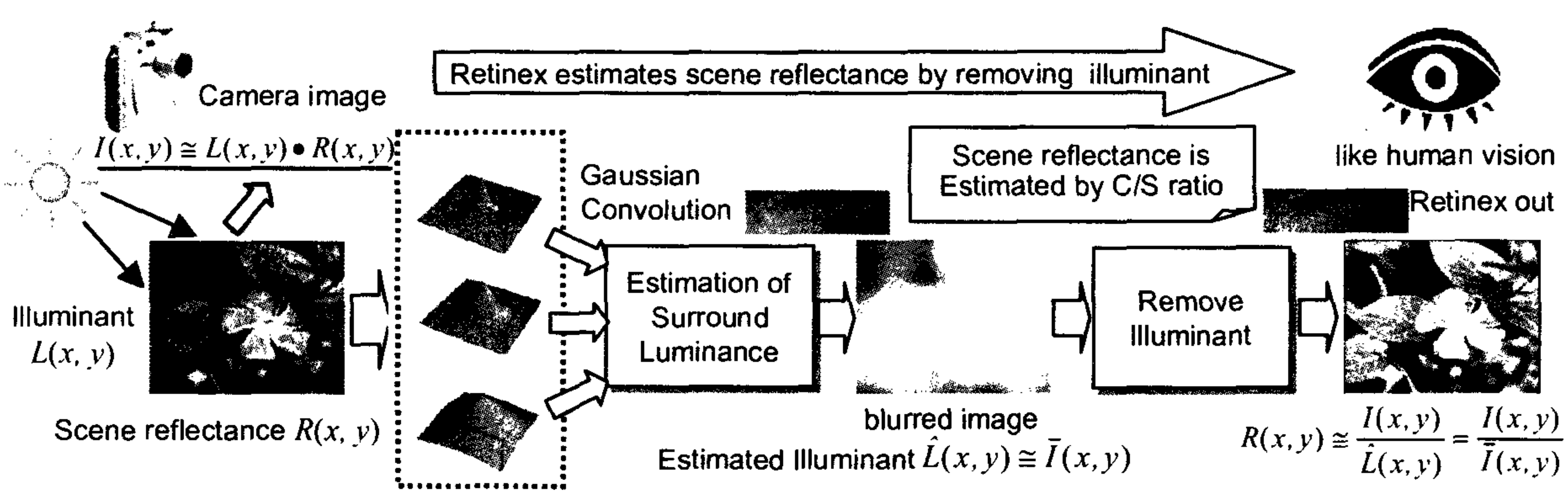

Fig.5 Principle of image appearance improvement by Multi-Scale -Retinex model

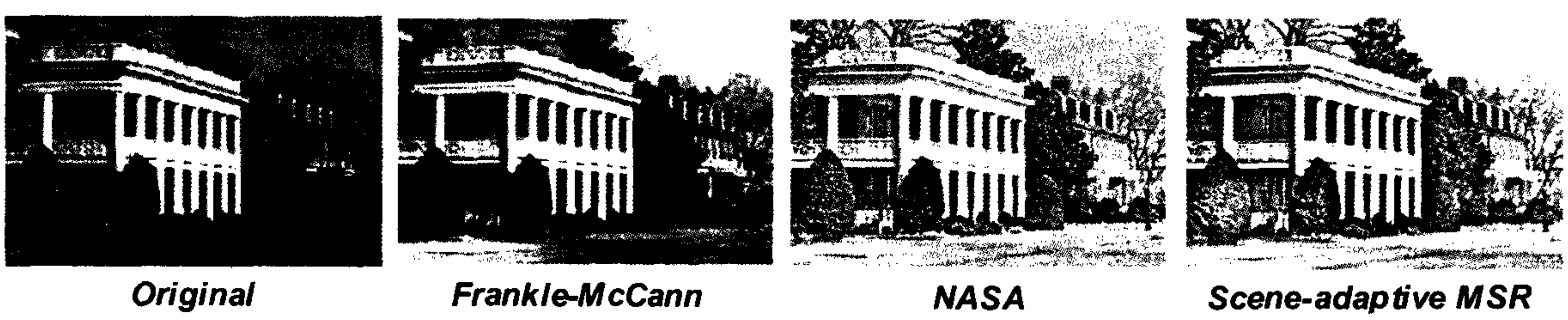

Fig.6 Visibility Improvement in Displayed Image by Adaptive Scale-Gain MSR.Model

4. Adaptive Gamut Mapping

The design concept of GMA (Gamut Mapping Algorithm) is basically divided into the following two categories.

(1) D-D(Device-to-Device)GMA

(2) I-D(Image-to-Device)GMA

So far most of GMA application has been addressed to compress a wide gamut CRT image into a narrow gamut print image. While the gamut expansion from narrow to wide has not been interested so much, the printer color gamut has been much expanded with the improvements in ink and paper. Now the "Bi-directional" GMA from wide to narrow and narrow to wide is desired for the pleasant color imaging. In practice of I-D GMA, the image GBD (Gamut Boundary Descriptor) is necessary. We have developed a simple method called ***r-image*** for getting image GBD as shown in Fig.7. A set of the maximum radial vectors is extracted from the sub-divided segments in CIELAB polar coordinates and mapped onto 2D (θ, ϕ) plane as a B/W ***r-image***, where each pixel corresponds to the magnitude of each radial vector.

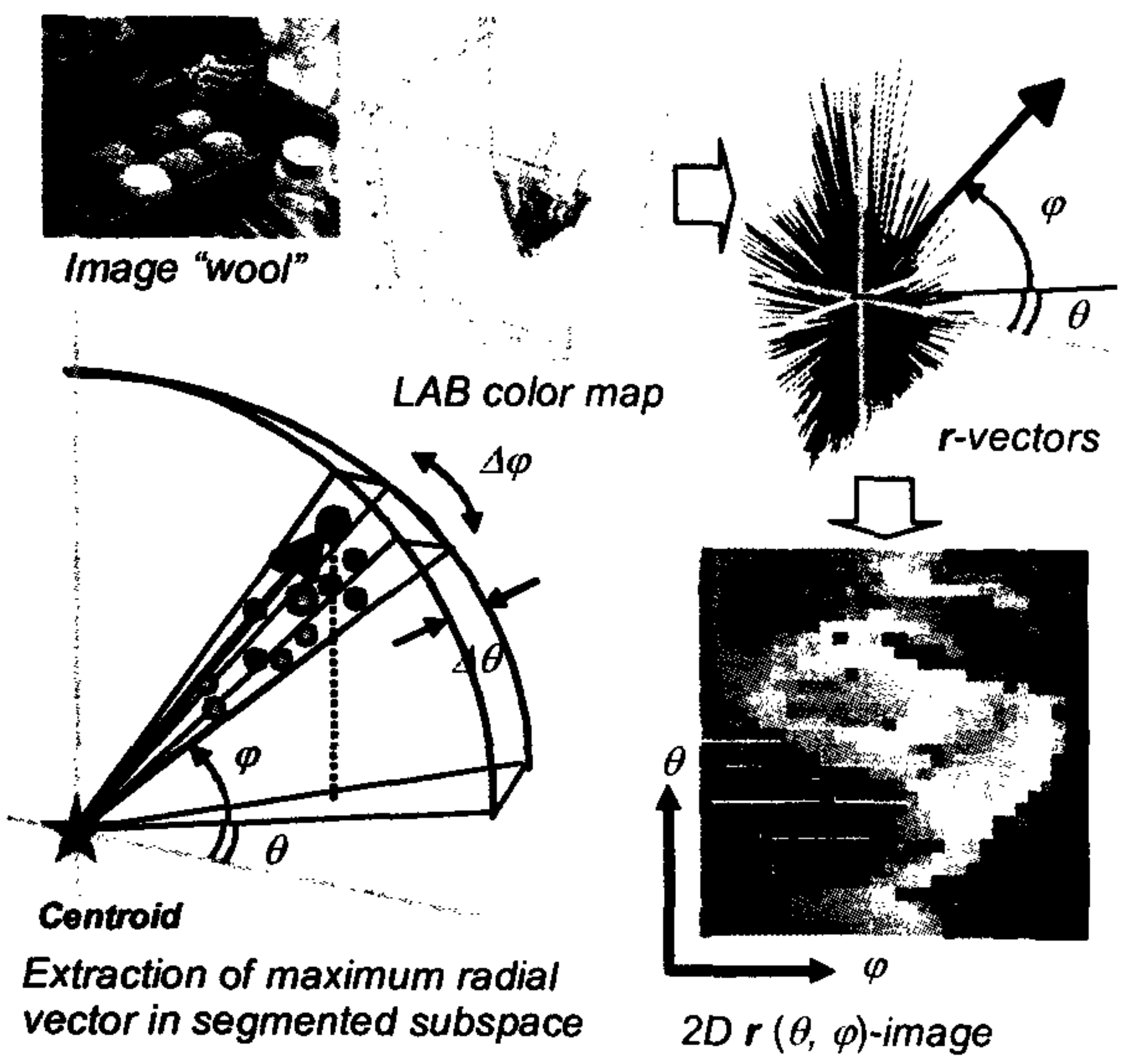

*Fig.7 Gamut Boundary Description by **r-image***

Since the out of gamut colors are directly discriminated by a "pixel to-pixel" comparison in the ***r-image*** between a given image and the output device (see Fig. 8), the bi-directional GMA is easily designed.

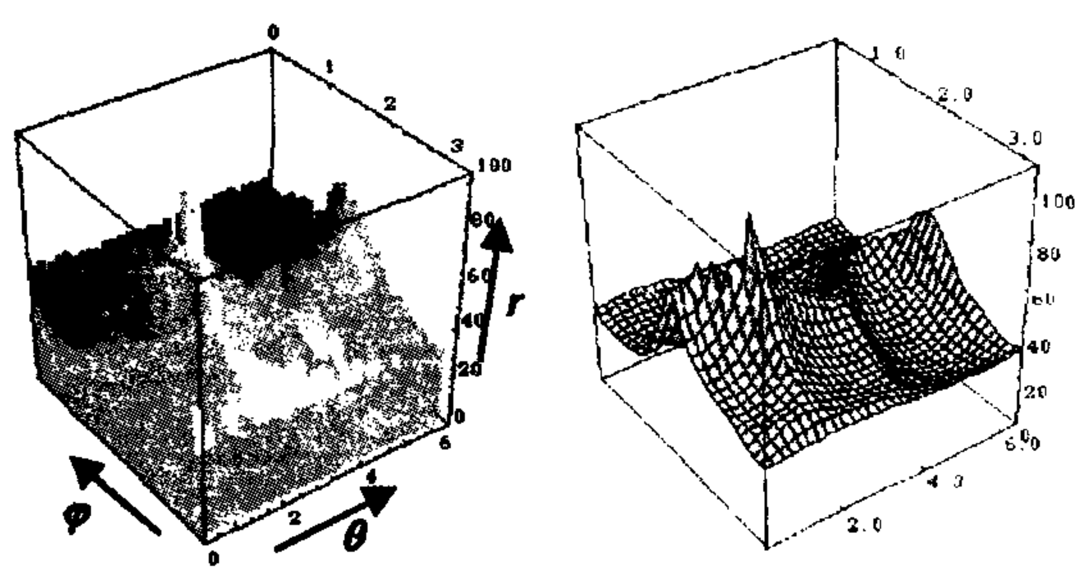

Fig.8 Image vs. printer gamut comparison

Fig.9 shows an improved image sample by "Gamut Expansion". Color appearance of narrow gamut scene captured under dim light is dramatically improved just as seen under light room by the gamut expansion. (a) is a scene under normal light and (b) is a test image under dim light. It is highly de-saturated and the colors are distributed in very narrow gamut. The color distribution of picture (b) under dim light was expanded as shown in (c) with the bright and vivid colors close to normal (a).

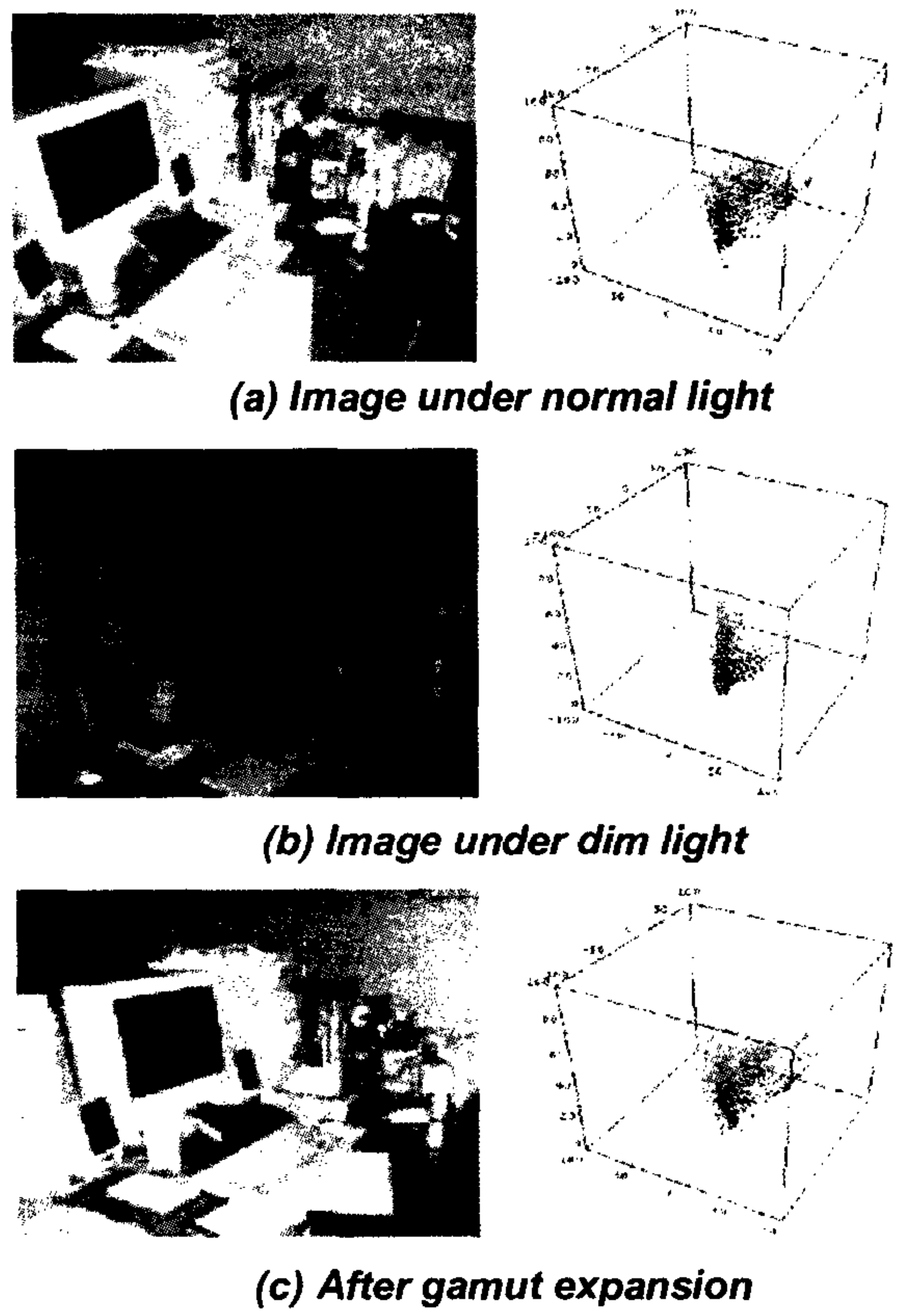

Fig.9 Appearance improvement by Gamut Expansion

5. Conclusion

In this paper we introduced a content-based and image-dependent approach to reproduce more pleasant images on display or printer. Ideal goal is to capture and reproduce a real world scene just as human vision is seeing. Collaboration with vision research is necessary for future work on intelligent image processing.

References

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