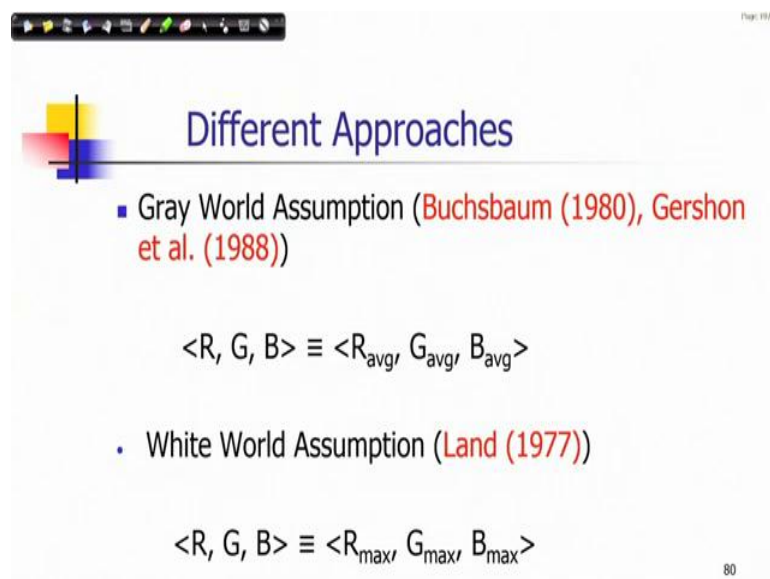


**Computer Vision**  
**Prof. Jayanta Mukhopadhyay**  
**Department of Computer Science and Engineering**  
**Indian Institute of Technology, Kharagpur**

**Lecture - 38**  
**Color Fundamentals and Processing (Part V)**

We are discussing about computation of color constancy and the objective is to get color representation which would be invariant to the color of the illuminant.

(Refer Slide Time: 00:29)



Page 18/19

### Different Approaches

- Gray World Assumption (Buchsbbaum (1980), Gershon et al. (1988))  
$$\langle R, G, B \rangle \equiv \langle R_{avg}, G_{avg}, B_{avg} \rangle$$
- White World Assumption (Land (1977))  
$$\langle R, G, B \rangle \equiv \langle R_{max}, G_{max}, B_{max} \rangle$$

80

And for that there are two tasks that we have been identified we have identified; one task is to estimate the color of the illuminant. the next task is to transform the colors from the source color image to a target color image where there is a target illumination is desired I mean it should be color illuminated by a target illuminator. So, now, we will be discussing different approaches of estimating color of the illuminant.

So, you consider here that there is one technique which assumes that the world is gray. Which means that in the red green blue all these components if I average all the color then actually that color of the illuminant would be gray. So, this particular part we can describe in terms of red, green, blue. If I take the average of the red green blue components this one is giving you the color of the illuminant.  $\langle R, G, B \rangle \equiv \langle R_{avg}, G_{avg}, B_{avg} \rangle$

So, this is that types technique is a very simple technique you have to perform simply averaging of the color vectors and you get the estimation of the color of the illuminant. The other assumption is called white world assumption, so in this case the assumption is that the color of the illuminant will be given by the maximum of these components of red, green, blue.  $\langle R, G, B \rangle \equiv \langle R_{\max}, G_{\max}, B_{\max} \rangle$

The color is almost like white and you just consider the maximum of their red green blue component. And here you need to just compute the maximum of red components of all the pixels, maximum of green components of all the pixels, and maximum of blue components of all the pixels.

(Refer Slide Time: 02:19)

The slide is titled "Edge based color constancy computation" and features a small graphic of overlapping colored squares (red, yellow, blue) on the left. A bullet point states: "Extending pixel-based methods to incorporate derivative information". Below this, the formula for Minkowski's norm is presented: 
$$e^{n,p,\sigma} = \left( \int \left| \frac{\partial^n f_{c,\sigma}(x)}{\partial x^n} \right|^p dx \right)^{\frac{1}{p}} = k e_c$$
 The formula is annotated with labels: "Order of derivative" points to  $n$ , "Scale" points to  $\sigma$ , "Type of norm" points to  $p$ , and "Minkowski's norm" points to the entire expression. A label "Color image component (channel c)" points to  $f_{c,\sigma}(x)$ . The slide number "81" is in the bottom right corner.

So, these two are very simple techniques, there are other techniques which use a more involved competitions and assumptions are bit different here. Here it is considered that the pixels which are lying on the edges, color of the illuminant they are more information of the color of the illuminant.

So, the idea is that when colors are reflected by the boundaries of objects, you get kind of a specularly and as we discussed that specular reflection contains the color of the illuminant. So, from there itself we are trying to estimate the color of the illuminant. So, one of these method that is shown here, it extends pixel based methods to incorporate derivative information.

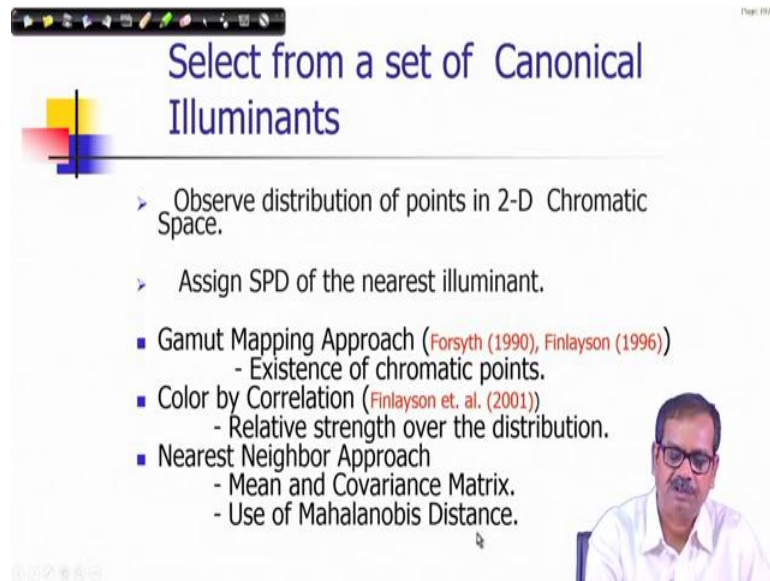
That means, again you are trying to accumulate all such pixels intensity values or their derivatives of those intensity values. And then this aggregated form itself will give you the proportional color representations in the three vectorial (Refer Time: 03:25). So, you just consider these particular computations.

And here you can see that we are considering n-th order derivative of a intensity value which is represented by the function  $f(x)$  and  $c$  is the channel I think I have. So,  $n$  is the order of the derivative, then  $p$  is a type of norm as you can see this is like an  $L^p$  norm. And this is also called Minkowski's norm in the continuous space. And  $\sigma$  is the scale; that means, it is smoothen by a Gaussian mask and then you are performing this derivative. And then you compute this particular competitions of  $L^p$  norm or

Minkowski's norm. 
$$e^{n,p,\sigma} = \left( \int \left| \frac{\partial^n f_{c,\sigma}(x)}{\partial x^n} \right|^p dx \right)^{\frac{1}{p}} = ke_c$$

And for that particular channel see, so if you are doing it for red component for example, all the pixels then you will get a value which is proportional representation of the illuminant for that particular channel. And you carry out this competitions for every channel like green and blue you will get three such values and their proportional values will represent the color of the illuminant. And you can adjust your particular intensity of that illuminant and transfer the color using the color correction as I discussed in the in previous slides in the previous lecture.

(Refer Slide Time: 04:49)



**Select from a set of Canonical Illuminants**

- Observe distribution of points in 2-D Chromatic Space.
- Assign SPD of the nearest illuminant.
- Gamut Mapping Approach (Forsyth (1990), Finlayson (1996))
  - Existence of chromatic points.
- Color by Correlation (Finlayson et. al. (2001))
  - Relative strength over the distribution.
- Nearest Neighbor Approach
  - Mean and Covariance Matrix.
  - Use of Mahalanobis Distance.

The other kind of approach could be that instead of computing the colors or accumulating the responses of the perceived specularities in pixel reflections. What we can do? We can consider something some kind of data driven approach; that means, we have some models of different canonical illuminants in terms of their RGB distribution. Distribution in a color space, it could be RGB space, it could be xy space.

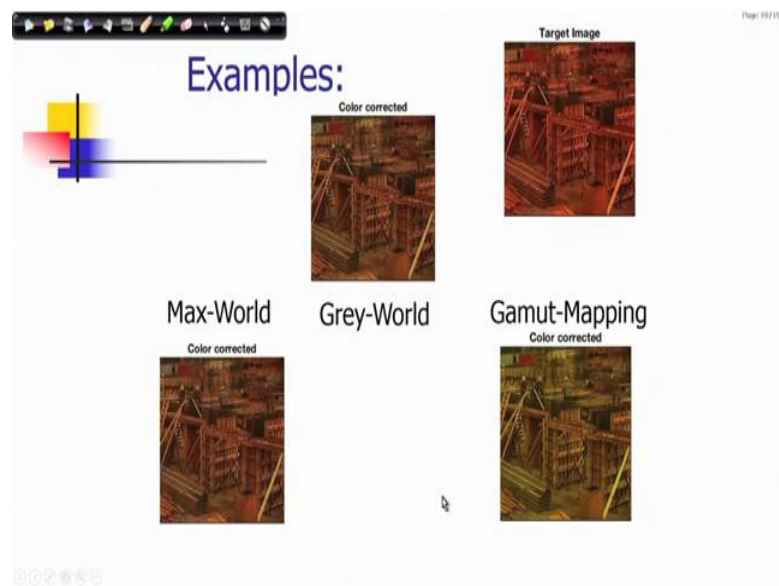
And then given an image we try to find out what kind of distribution is there in that space. So, the similarity between these two distributions can indicate that whether that corresponding scene has been illuminated by that given illuminant whose distribution is known. So, if I have a set of such illuminants we would try to consider the illumination with the nearest of them.

The closest approximation of the distribution what we get we try to attach that illumination for that scene in that way we can select is from a set of canonical illuminant. So, it is observe distribution of points in 2D chromatic space even you can do it in 3 D chromatic space also and; that means, including intensities; then you can assign the spectral power density of the nearest illuminant to them.

So, there are approaches like gamut mapping approaches, so as we have discussed that how xy chromaticity chart gives you a gamut. That means, the distribution of points in this particular space which should be lying in a triangle and from there you can compare the that distribution with the distribution of the canonical illuminants.

So, existence of chromatic points is important, color by correlation is another approach. So, it depends upon you know what kind of similarity, how do you compute this similarity, so it is relative strength over the distribution that is considered. You can use also nearest neighbour approaches like, you can use mean and covariance matrix of those distributions and some distance functions like mahalanobis distance function you can use. So, in this way you can select one of this canonical illuminants.

(Refer Slide Time: 07:23)

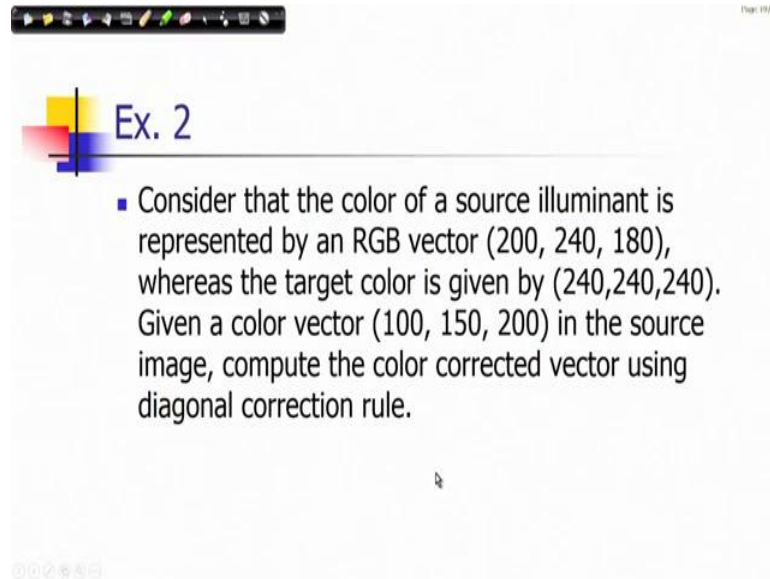


Some examples of these techniques, consider this is a target image and which means this image is illuminated as you can see there is a reddish hue in the illuminant. And that is why their color is more tending towards red. But, for if I perform color corrections and first you estimate the color of the illuminant using grey world assumption.

That means you consider averaging of the red component, green component and blue component use it as the color of this image. And if I use the target illuminant as simple white light like with the intensity value say (255, 255, 255). And then perform color correction following diagonal correction rule then you will get this image.

So, this is for grey world method, for max world method you get this kind of image and gamut mapping will give you this kind of image. I have not described in details gamut mapping you can go through some of the papers. And in our course or in this particular respect we will be considering simple approaches of estimating colors using say grey world assumption, max world assumption etc.

(Refer Slide Time: 08:50)



Ex. 2

- Consider that the color of a source illuminant is represented by an RGB vector  $(200, 240, 180)$ , whereas the target color is given by  $(240, 240, 240)$ . Given a color vector  $(100, 150, 200)$  in the source image, compute the color corrected vector using diagonal correction rule.

So, let me discuss a problem here to let me solve a problem just to show you that how color corrections could be performed using source illumination and target illumination. So, let us consider this exercise and then we can understand the computational steps better. So, consider that color of resource illuminant is represented by an RGB vector  $(200, 240, 180)$ , which means 200 is red component, 240 is a green component and 180 is the blue component.

Whereas the target color is given by  $(240, 240, 240)$  in my case as you can see in this example it is trying to get a white illuminant by with this combination that is the target. And given a color victor  $(100, 150, 200)$  in the source image compute the color corrected vector using diagonal correction rule, so this is a problem statement.

(Refer Slide Time: 09:55)

**Ans. 2**

■ Diagonal Color Correction

$$k_r = \frac{R_d}{R_s} \quad k_g = \frac{G_d}{G_s} \quad k_b = \frac{B_d}{B_s} \quad f = \frac{R + G + B}{k_r R + k_g G + k_b B}$$
$$R' = f k_r R \quad G' = f k_g G \quad B' = f k_b B$$

$(R_d, G_d, B_d) = (240, 240, 240)$      $(R_s, G_s, B_s) = (200, 240, 180)$

$k_r = 1.2$     $k_g = 1$     $k_b = 1.33$     Color:  $(R, G, B) = (100, 150, 200)$

$$f = (450) / (120 + 150 + 266) = 450 / 536 = 0.8396$$

Color corrected vector:  $R = .8396 \times 1.2 \times 100 = 100.75 = 101$  (Handwritten: 450)

$G = .8396 \times 1 \times 150 = 125.94 = 126$

$B = .8396 \times 1.33 \times 200 = 223.33 = 223$

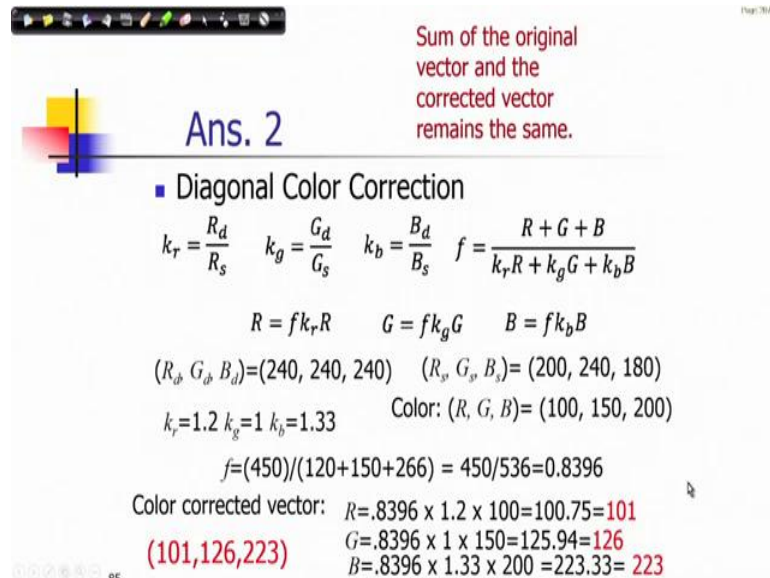
So, let me see how we can perform this competition it is quite simple and quite direct if you know this expressions as I mentioned. We need to first compute the proportional factors of target and source colors of the illuminants for each primary components like  $k_r, k_g, k_b$  you need to compute. And also you need to compute the corresponding factor for normalizing the colors. So, their intensity value remains still the same.

So, and then the expressions, so a modified colors are given in this form since they are modified I am using once again this notations. And if I perform this computations what is given you can see  $(R_d, G_d, B_d)$  is given and the component of source is also given. So, if you component this proportional factors by using this information those values are shown here. Then this color has to be converted into a form as if it is illuminated by the source given by  $(R_s, G_s, B_s)$  that means,  $(240, 240, 240)$ .

So, the completion of f is this is the factor which is computed here and so color corrected vector as per these expressions R. You can see R becomes 101, it was earlier 100, now after modification, it is 101, green becomes 126 and blue becomes 223, so these are the modified color corrected values. So, you should note that the intensity in this particular computation if I add  $(R + G + B)$  if I add these values and that is still coming the same which is actually with this value is 450.

So, if I add 101, 126, 223, you will still get 450, so in this correction you are not changing the intensity values of the modified pixels. but what you are changing you are changing the relative proportion of three primary components because it is corrected for the target illuminant, so that is how we perform the color correction.

(Refer Slide Time: 12:27)



**Ans. 2**

Sum of the original vector and the corrected vector remains the same.

■ Diagonal Color Correction

$$k_r = \frac{R_d}{R_s} \quad k_g = \frac{G_d}{G_s} \quad k_b = \frac{B_d}{B_s} \quad f = \frac{R + G + B}{k_r R + k_g G + k_b B}$$

$$R = f k_r R \quad G = f k_g G \quad B = f k_b B$$

$(R_s, G_s, B_s) = (240, 240, 240)$      $(R_d, G_d, B_d) = (200, 240, 180)$

$k_r = 1.2$     $k_g = 1$     $k_b = 1.33$     Color:  $(R, G, B) = (100, 150, 200)$

$$f = (450) / (120 + 150 + 266) = 450 / 536 = 0.8396$$

Color corrected vector:

$$R = 0.8396 \times 1.2 \times 100 = 100.75 = 101$$

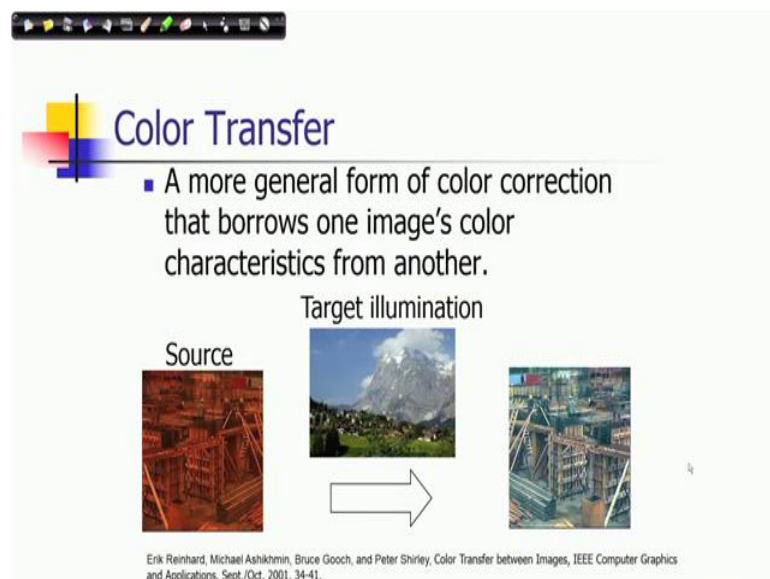
$$G = 0.8396 \times 1 \times 150 = 125.94 = 126$$

$$B = 0.8396 \times 1.33 \times 200 = 223.33 = 223$$

**(101, 126, 223)**

So, this is the final answer in this problem and as I mentioned some of the original vector and corrected vector remains the same.

(Refer Slide Time: 12:33)

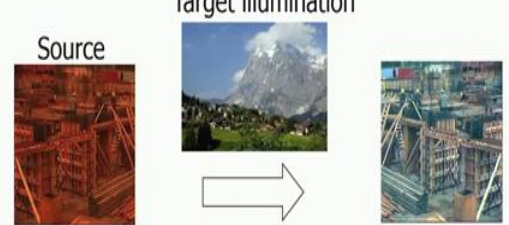


**Color Transfer**

■ A more general form of color correction that borrows one image's color characteristics from another.

Target illumination

Source



Erik Reinhard, Michael Ashikhmin, Bruce Gooch, and Peter Shirley, Color Transfer between Images, IEEE Computer Graphics and Applications, Sept./Oct. 2001, 34-41.



We will discuss about a more general form of color correction and that operation is called color transfer. In this operation what it does that there is an source image which has its own color distribution and there is another image which defines a target color distribution. So, the source image would like to borrow their target distribution in its own rendition.

So, an example can be cited here to explain this particular operation, consider this is an image which is that source image. And you can see that source image has an illumination which is a bit reddish illumination and all the objects inside it they are affected by that particular illumination.

Consider another image which is a completely different image having different types of objects, different scenario, different context, but it defines a an illumination or defines a target illumination, or target color distribution which is depicted by this target image. So, it is an image of alps, a peak of alps and, so this distribution should be transferred to the content to the objects of source image to the display of source image, so that it looks like this.

So, your image under this transferred illumination model or if I said with the transferred color characteristics that would look like this. So, here you can see the colors are quite different and distribution is quite akin to the target illumination of the as if they are illuminated by the illumination of target image.

(Refer Slide Time: 15:06)

**Algorithm**

Convert RGB to an opponent color space.

LMS-cone space  $\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$

$L = \log L$   
 $M = \log M$   
 $S = \log S$

Opponent color space (A variant)  $\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix}$

So, let us discuss about the processing of this particular operation. So, what we do here we process all this pixels in a different color space where we can separate out the chromatic components from luminance component. So, in this particular technique this is the way this processing has been done. first, RGB is the color space where the color values of the pixels are captured.

So, there convert it into another space which is called LMS cone space, so it is trying to model our retinal sensitivity of different cones. So, this model trying to provide as if the sensations which will be generated in our cones. And that is what it is trying to capture with this mathematical model, you can see it is a linear transformation.

And just to remind you that L stands for long wavelength, M stands for medium wavelength and S stands for short wavelength which means they are corresponding to red, green and blue zones of the spectral domain. Now, once you get this LMS value you further process it you take it to their log domain. Because, in some of the perceptual models it is considered that our perception is more it follows the logarithmic, it is proportional to the logarithmic value of the receipt sensory unit sensory single or receipt energy.

So, that kind of heuristics have been used here. we use the logarithmic values and use this logarithmic values to separate out the chroma components for the luminance components. So, you can see once again another transformation which is also a linear transformations in the logarithmic with the logarithmic values of the cone responses that we have considered in all model.

We call it LMS once again, but their font has been shown in a bold font and you can see

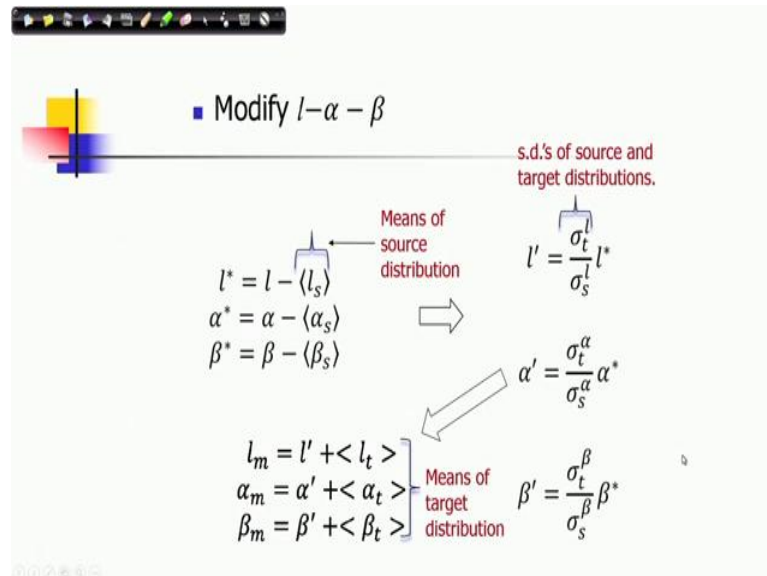
the color space which has been given by  $\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix}$ . These are the three components which is

similar to an opponent color space model you can see particularly in this row. So, this is corresponding to the intensity component which is the addition of L, M and S and this one it is  $(L + M - 2S)$ , so L corresponds to red, M corresponds to green.

So, it is like yellow minus blue that kind of model opponent color model and this is  $L - M$  which is red minus green opponent color model which we have already discussed

earlier. So, it is a variant of this particular operation processing this particular opponent color space, so we perform this kind of separation. Now, in the next ; we will be doing will be performing certain processing over the chromatic components. So, that you can transfer the distribution of colors in the target image to the source image, let us see how we can do it.

(Refer Slide Time: 19:19)



So, for modifying the chromatic component and also the luminance component, first what we can do that, we subtract the mean of all those components from the source image. So, you can see here this symbols  $l_s$  ,  $\alpha_s$  ,  $\beta_s$  they denote the corresponding  $l, \alpha, \beta$  components of source image. And then you are taking their mean which is denoted by this angle bracket operations I mean this is the symbol just.

So, your subtracting those means and then up the subtracted values they are scaled up, so that the standard deviation of the target distribution can be transferred. I mean your source distribution also should follow the standard should be similar to this variances or standard divisions of the target distribution. So, you perform a proportional scaling- a scaling proportion in proportion to their ratios of standard deviations that could make these operations.  $l' = \frac{\sigma_t^l}{\sigma_s^l} l^*$  ,  $\alpha' = \frac{\sigma_t^\alpha}{\sigma_s^\alpha} \alpha^*$  ,  $\beta' = \frac{\sigma_t^\beta}{\sigma_s^\beta} \beta^*$

So, you can see here, this is the standard deviation of the luminance component of the target image. And this is a standard deviation of the source component of the luminance component of the source image. So, if I multiply the modified luminance value with this scale with this ratio or with this proportional factors. Then actually your making the standard deviation of the modified distribution is the same as the standard deviation of the target distribution.

So, that is what your performing by doing this particular operations and you are doing it for every component in the same way. So, the corresponding ratios of the standard deviations in those components in both target and source those are multiplied with the modified values. So, this can transferred the standard deviation operation also this is what it is just defines the corresponding symbols as I mention that they are the standard deviation of source and target distributions and defining those ratios.

So, once you have performed this then you have to also add the mean of the target distributions components which means for the luminance components,  $\alpha$  component, and  $\beta$  component. So, in this way in the transferred domain, transferred color space or transferred colored values of source image in that distribution you have transferred the mean.

So, that distribution we have the mean which is equal to the mean of the target illumination, target distribution and also it will have the standard deviation of the target distributions. And that is in the  $l - \alpha - \beta$  space. And now the rest of the job should be that you perform the inverse transformation to take all these components back to the RGB domain. So, for that what you should do; you should follow the inverse operations.

(Refer Slide Time: 23:33)

**Convert back to RGB**

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -1 \\ 1 & -2 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} l_m \\ \alpha_m \\ \beta_m \end{bmatrix}$$

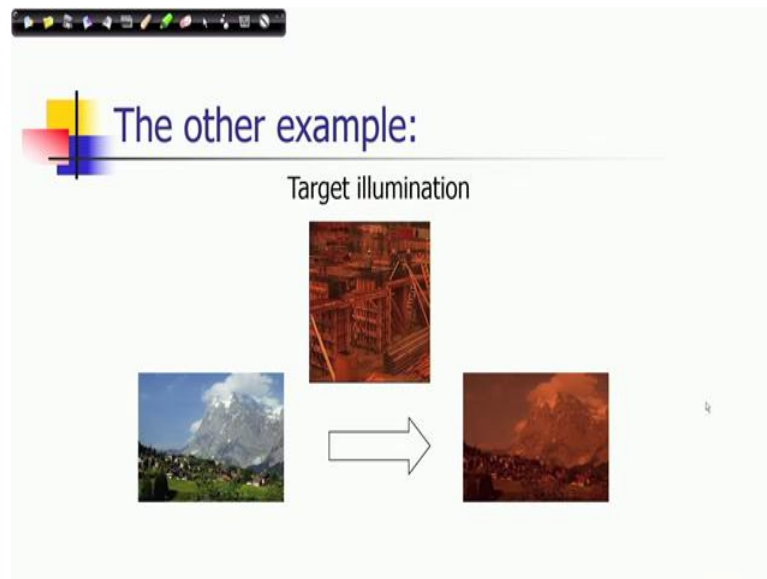
$L=e^L$   
 $M=e^M$   
 $S=e^S$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 4.4679 & -3.5873 & 0.1193 \\ -1.2186 & 2.3809 & -0.1624 \\ 0.0497 & -0.2439 & 1.2045 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix}$$

That means you can see that after modifying the  $l, \alpha, \beta$  components again you are perform you are taking those values into the this place **L M S**. But this is a logarithmic space of L M S cone color space, so this is a logarithmic of L M S cone color values. So, far from there again to you have to transfer to the original L M S cones color space.

So, you perform the exponentiation operations over those logarithmic values and perform once again the inverse operations to transfer from L M S to the R G B value. So, in this way you get the color transferred image from the source image using the characteristics or using the distribution of the target image. So, let me give you the other example of this operation.

(Refer Slide Time: 24:51)



In this case we will be considering we will show off the source and target images and we will see its effect which means your target illumination will be defined by the image which has that reddish illumination in the environment. And your source image will be the image which has been captured in broad day light in a every sunny day. And it is a once again its content it has been shown its a mountains peak which is very prominent and there is a valley, green valley which has been also displayed. So, under the color transfer operation let us see how it looks.

So, we can see actually the scene is perceived that it has been captured in some you know reddish under some reddish illumination which for natural scenery may considered that it is bit unnatural in that sense it should not be, so much of reddish. But that is what the color transfer operation did, but it would be near you can say sunset kind of operations. So, this is just the imaginations through which you can perceive this kind of image.

(Refer Slide Time: 26:22)

## Color Demosaicing

- Use of color filter array (CFA) in a single chip CCD camera.
- Generation of dense pixel maps from sparse data by interpolation.
- Hardware cost and computation time to be kept low.

**BAYER'S**

G	R	G	R
B	G	B	G
G	R	G	R
B	G	B	G

**KODAK**

G	B	G	R
R	G	B	G
G	B	G	R
R	G	B	G

So, next type of processing that we are going to discuss that is the color demosaicing operation, so in this problem we use a color filter array. So, first let me explain the principle of the single chip camera where actually we know that for a camera we required three types of filters. For a normal camera when we have full color reception which means you have a color signal, suppose there is a color signal and then you have to receive the signal in the form of a sensor.

(Refer Slide Time: 27:00)

The diagram shows a lens focusing light onto a sensor array. The sensor array is divided into three regions labeled R, G, and B, representing Red, Green, and Blue filters. The diagram shows how light from a single point is captured by multiple filters, leading to a sparse sampling of the color signal. The text "G=?" and "B=?" indicates the need for demosaicing to reconstruct the full color signal.

So, same signal should be received by three different sensors, say there are red, green, and blue and there are different techniques by which the same optical signal is guided to this or they are divided into three different parts. And then they are sensed by three different sensors independently. But it has to be the same coherent source and that coherency has to be maintained to represent the color of a particular object which should be received by the same signal.

Now, this kind of technology is quite complex and there are different ways people do it where they have that optical divider and like using prisms etc.. And the manufacturing of this kind of camera is requires high technological innovations and it is quite costly. And since you are using for each pixel three different sensors, we call it three chip colored camera or three chip sensors.

But there is a cost effective technology for sensing color images where instead of three sensors, I will be using only one of them. That means, I can use either red, I will be only sensing red or I will be sensing sometimes green or sometimes blue. But whenever I am sensing the signal whenever the camera is sensing this any signal of a coming from a particular point, it only captures only one component, but what it does, it does in an interleaved fashion. So, which means that in an image suppose from the image perspective if I record the corresponding received energies from different color channels.

At this point I will have only red whereas, next point I will have say green and say this point is blue. So, you can see that I will be losing my spatial resolutions, but if I assume my spectral resolution is much coarse; that means, I can associate this blue also to this pixel and this green to this pixel. So, I can consider at all this pixels they have the same R G B values, so this is a very crude way of estimating the colors.

So; that means, assigning colors of each pixels all the full color information estimating full color information's along this pixels. As you can see it is a very crude, because I am simply transferring the values of missing components to the neighboring pixels by considering the spatial correlation of the spectral channels.

Now, this problem itself I have just given you one particular solution, but there could be many solution it is an interpolation problem which means I have the missing components and missing components at this point. So, for this pixels say for example, for this pixels



if it is I am recording only red, so my green and blue they are missing. but in the neighborhood I have some pixels where those values are there some are green, some are blue say some are green, some are blue.

So, even I have also other red also, so considering this neighborhood pattern or this neighborhood information how best I could estimate this missing components that is the problem of color interpolation. And when we sense the image in this interleaved fashion of one of the spectral components we call that kind of image as a color filter array. So, let me go back to my slides, so that to summarize this particular computation problem and this kind of computation is known as color demosaicing or color interpolation.

The term demosaicing came as if the pattern interleaved pattern is called as a mosaic pattern with different color components. So, here we can see that in this problem you are using color filter array of a single chip CCD camera, from there you are generating a dense pixel maps of all the color components. So, they have sparse data as if as you have only one component at every point, but you would like to get all the color components for every point.

And as the motivation as I mentioned the technologically it is simpler to design and manufacture this kind of cameras. Because you know the spectral coherency of the reception to ensuring that coherency is not required here. So, we have you can use simply the filters in front of the images in front of your lens color filters which are in patterns. And for each pixel you will be receiving only energy in that spectral band.

So, there are different patterns are proposed by which you can design this filters that is why the array also is called color filter array. Because those are sensed by incident light through this filters. So, this example of this patterns are shown here, you can see in this pattern which is called Bayer's pattern and which is a very popular pattern in most of the literatures you will find people have worked on this pattern. And you can see that in this pattern what happens that green, red green red, so they are interleaved in one row.

In another row blue, green, blue, green they are interleaved, so the fact is that green has been sampled in the color filter array twice the red than red and blue. So, this is one consideration is that green anywhere more sensitive to the green channel. So, lots of

information of green channel will affect more than the other two components that is why we have this kind of sampling pattern.

But this is not the only pattern we can have other kind of patterns for example, there is a pattern adopted by Kodak , famous Kodak cameras. So, there you have this patterned like in the same row you have green, blue and reds on the same row this patterns are interleaved. Whereas, Bayer's pattern now we can also identify as if this is the red row because green is sampled in every row, but in one row when red pixels are sampled then the next row the blue pixels are sample.

So, rows can be you know denoted by for the purpose of describing this pattern or computations we can save a pixel in the red row or blue row and whereas, columns could be green and non green, so either it is red or blue. So, in this way you can identify a location in the Bayer's pattern; you should note also the starting pixel locations and the starting row, starting column and starting rows state. If I can provide you that and given this particular rule then I can describe the all the patterns.

So, in the color demosaicing problem, it is the pattern which is which remains a fixed, so you know already that given a color filter array for each pixel which is the spectral component of that particular image. So, for any every pixel I know that which spectral component it is, whether it is green, red and blue. And by following this pattern if I can tell you one particular pixel the rest of the pixel's spectral components can be determined or described.

So, this is the advantage when you use this kind of regular pattern when you describe a color filter array. So, our objective here is to interpolate the pixel values in such a way that you get all the full color components; that means, all three components at every pixel and that is what is a computation of color demosaicing. So, let me stop here and we will continue this discussion in the next lecture we will discuss about different algorithms for performing this color demosaicing. So, let us give a break at this point.

Thank you very much for your attention.