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White balance in inspection systems with a neural network

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Automatic inspection systems based on image processing have been used in manufacturing systems. However, in the case of systems using colour images, colour signals fed into the system through a camera depend upon the inspected objects and on the light sources. Accordingly, it is necessary to convert the colour signals received under the illumination at the time of inspection into those that would be received when using a standard light source to achieve a reliable and versatile inspection system that can operate stably under a wide variety of light sources. In this paper, a colour image input system with white balancing using a neural network is proposed, and compared with that used in ordinary video cameras by means of computer simulation. This system is applicable as the pre-processor of colour signals for automatic inspection systems based on colour image processing. Copyright © 1996 Elsevier Science Ltd.

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Introduction

In recent years, automatic inspection systems based on image processing have become increasingly important, especially for computer aided manufacturing, because they can enhance speed of inspection and also record useful information to analyze conditions of the production line. Many vision systems are constructed with black and white cameras, and are mainly used to inspect the shape of objects. However, using colour cameras it is possible to make more intelligent inspection systems that can analyze, understand and inspect images of objects with greater precision.

When this sort of inspection is carried out by human beings, they can determine the actual colour of the object with reasonable accuracy whether the object is lit by an incandescent bulb, a fluorescent light, or natural daylight[1]. This is because human perception adapts to the spectral characteristics of the light source; this characteristic of human vision is called *chromatic adaptation*[2].

However, the colour information fed to an inspection system from a camera will vary with changes in light source, even if the camera continues to look at the same object. As a result, to achieve a more reliable and versatile inspection system that can operate stably under a wide variety of light sources, it is necessary to convert the colour signals received under the illumination at the time of inspection into those that would be received when using a standard light source.

In ordinary photography, the differences between the colours perceived by the human eye and the actual colours that would be registered by a colorimeter are compensated by selecting a suitable film or adding filters to suit the lighting conditions. Conventional video cameras use a simple auto-white balance function, with practically acceptable performance for hobby uses[3].

Since the colour adaptation of the human eye results from processing carried out within the brain, it should be possible to achieve similar results from a back-propagation neural network. Based on these ideas, we have developed a new white balance function that uses a four-input, three-layer, three-output neural network to which are input the colour temperature of the light source and the three primary colour signals of the received image[4].

This paper compares the white balance correction performance of this neural network with the conventional white balancing technique that is used, for example, in video cameras.

White balancing

We will first consider the basic principles of white balancing as carried out in video cameras. *Figure 1* shows a model of the imaging process within a video camera. In the camera, light reflected from the object is separated into the three primary colours (red, green

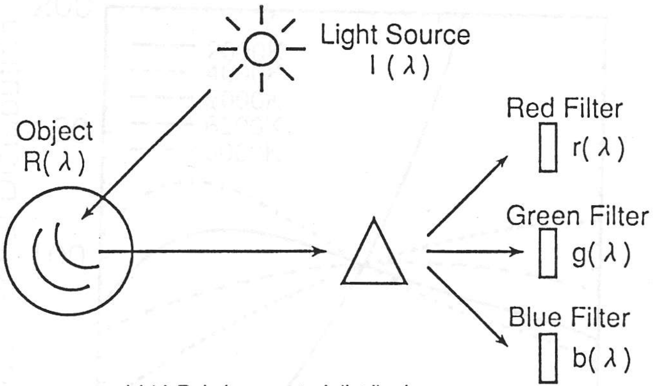

Figure 1 Model of colour camera

and blue), which are output separately. Representing the wavelength of light as λ, we consider the case of an object of reflectance $R(\lambda)$ in a light source with a spectral distribution of $I(\lambda)$. Light from the object is converted into red, green and blue outputs of r, g and b by an imaging system with corresponding responses of $r(\lambda)$, $g(\lambda)$ and $b(\lambda)$. The values of r, g and b can be expressed by the following set of equations:

$$\begin{aligned} r &= \int I(\lambda)R(\lambda)r(\lambda)d\lambda \\ g &= \int I(\lambda)R(\lambda)g(\lambda)d\lambda \\ b &= \int I(\lambda)R(\lambda)b(\lambda)d\lambda \end{aligned} \quad (1)$$

These equations are solved by integrating over the range of visible wavelengths. In this model, we assume that inspection is performed using a light source with a spectral distribution of $I_1(\lambda)$, resulting in red, green and blue outputs of r_1, g_1 and b_1.

White balancing is achieved by using the three outputs r_1, g_1 and b_1 to estimate those of r_0, g_0 and b_0 that would be obtained with a standard light source having a spectral distribution of $I_0(\lambda)$.

White balancing in video cameras

Figure 2 illustrates the through-the-lens (TTL) white balancing method used in most video cameras. In this method, the averaged output voltage of the imaging elements is used as an indication of the colour temperature of the light source, and variable-gain amplifiers that amplify the red and blue signals are adjusted accordingly. The colour temperature of the light source is estimated based on the empirical rule that, if one averages all the image signals obtained from the entire object under view, the resulting colour will be grey. However, simple averaging of the signals in an image can result in large errors in estimating the colour temperature when large parts of the image are taken up by objects of a particular colour. The weighted average based on fussy inference has been reported to be effective for improving accuracy in the estimation[5].

White balancing with a neural network

White balance correction is thought of as consisting of two stages: (1) estimation of the light source characteristics; and (2) correction of the colour signals based on these estimated characteristics[6]. The characteristics of the light source should ideally be represented by means of its spectral distribution, but in practice they are often represented more simply as a colour temperature.

In this paper, we consider the quality of white balance that is achieved when the colour signals are processed after separation. We compare the use of two colour signal processing methods: using a neural network, and adjusting the RGB gain factors. We assumed the light source to be a full radiator, and that its colour temperature had already been determined.

Experimental method

Data preparation

The following experiments were all carried out as computer simulations. The raw data used for these experiments was prepared as follows.

Light source. The D_{65} is specified in the CIE (Commission Internationale de l'Eclairage) standard and JIS (Japan Industrial Standard) Z 8720 as a standard light source of which the colour temperature is 6500 K. In our experiments, we chose the standard light source as a full radiator with a colour temperature of 6500 K. We also assumed that observation was performed using non-standard illumination from full radiator light sources with colour temperatures of 2000 K, 3000 K, 4000 K, 5000 K, 6000 K, 7000 K and 8000 K. Spectral characteristics of the main light sources used in these experiments are shown in *Figure 3*.

Colorimetry. We selected 35 standard colours from the following two groups of colour cards:

1. Macbeth Color Checker[7]: 24 colour patches.
2. Mansel Book[8]: 11 colour patches.

The Macbeth Color Checker contains six shades of grey, 12 colours that closely resemble the spectral reflectivity of natural objects such as skin, sky and leaves, plus additive and subtractive primary colours,

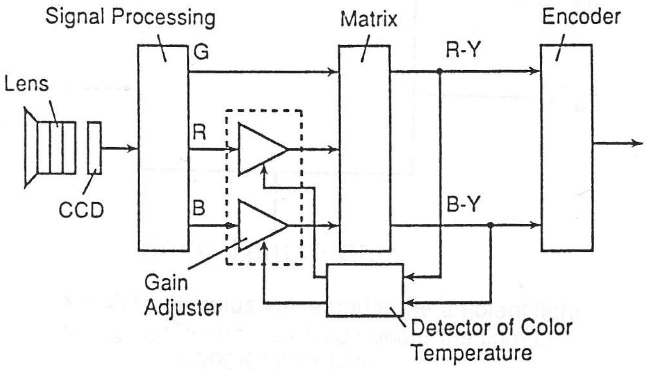

Figure 2 Automatic white balance of TV camera

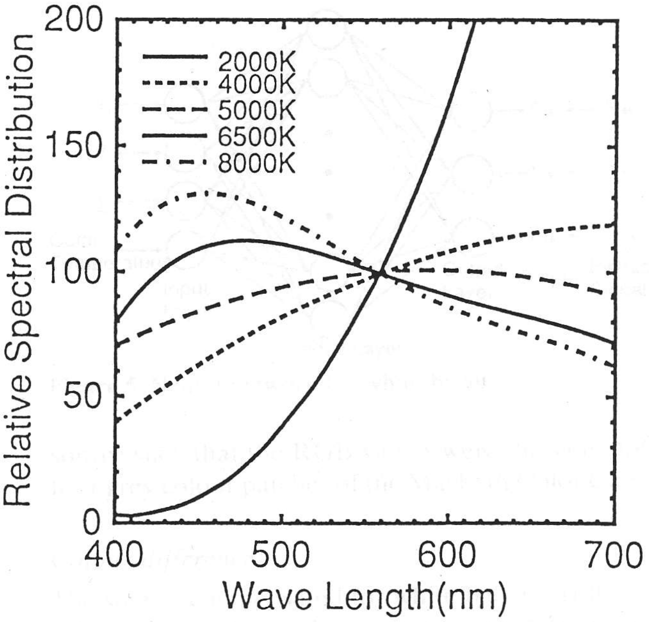

Figure 3 Relative spectral distribution of full radiator

red, green, blue, cyan, magenta and yellow. The Mansel Book is widely used as a source of colour samples, and 10 standard colours from the hue circle and a shade of grey were chosen as colour patches. We measured the spectral reflectance of these 35 colour patches using a Minolta CM-100 spectral colorimeter, which can measure the reflectance spectra over the range from 400–700 nm.

The colours from the Macbeth Color Checker were used to train the neural network, and the Mansel Book colours were used to evaluate the performance of the trained network.

Imaging system. The colour of the light reflected from the colour patches was detected by three (RGB) imaging systems which have specific spectral characteristics, respectively. In this report, we used the colour matching functions for the tri-stimulus values X, Y and Z or X_{10}, Y_{10} and Z_{10} laid down in the standard of CIE or JIS Z8701. The colour matching functions represent the spectral sensitivity of the human eye, and can be regarded as colour filters in the simulation. Their characteristics are defined such that the tri-stimulus values R, G and B, which are based on the physiological primary colours, are related to the tri-stimulus values X, Y and Z as follows:

$$
\begin{aligned}
X &= 1.85995 \times R - 1.12939 \times G + 0.21990 \times B \\
Y &= 0.36119 \times R + 0.63881 \times G \\
Z &= 1.08906 \times B
\end{aligned}
\tag{2}
$$

The light reflected from an object of reflectivity $R(\lambda)$ when illuminated by a light source with a spectral distribution of $I(\lambda)$ can be converted into X, Y and Z components using the following equation:

$$
\begin{aligned}
X &= \int I(\lambda)R(\lambda)x(\lambda)d\lambda \\
Y &= \int I(\lambda)R(\lambda)y(\lambda)d\lambda \\
Z &= \int I(\lambda)R(\lambda)z(\lambda)d\lambda
\end{aligned}
\tag{3}
$$

Here, $x(\lambda)$, $y(\lambda)$ and $z(\lambda)$ are the colour matching functions for tri-stimulus values X_{10}, Y_{10} and Z_{10}.

Model of colour correction system

Colour correction is performed by converting the tri-stimulus values (X, Y, Z) of the light source that illuminates the object during imaging into the tri-stimulus values corresponding to a colour temperature of 6500 K (see *Figure 4*).

White balancing with a neural network. The neural network of back propagation algorithm is used for the white balancing. As shown in *Figure 5*, the colour temperature of the light source illuminating the object and the tri-stimulus values (X, Y, Z) of the corresponding image are input to the network, and the corrected tri-stimulus values for a colour temperature of 6500 K (X_{65}, Y_{65}, Z_{65}) are output. The network was constructed with four inputs, three outputs and a hidden layer of 30 elements.

Before the neural network was made to perform colour correction calculations, it was trained using known input and output signals. For this purpose we used full-radiator light sources with colour temperatures of 2000 K, 3000 K, 4000 K, 5000 K, 6000 K, 7000 K and 8000 K, and the corresponding X, Y and Z values of the 24 colour patches of the Macbeth Color Checker as input signals, and X_{65}, Y_{65} and Z_{65} values obtained with a 6500 K full-radiator light source as output signals. Each of the X, Y and Z values of colour patches can be determined from the set of equations (3) based on the spectral reflectivity measured in advance.

White balancing by controlling the RGB gain factors. In white balancing in ordinary video cameras, the gains of the R and B channels are controlled such that total input signals for an image is always maintained at a neutral shade of grey, i.e. $R = G = B$. In these experiments, we adjusted the settings for each light

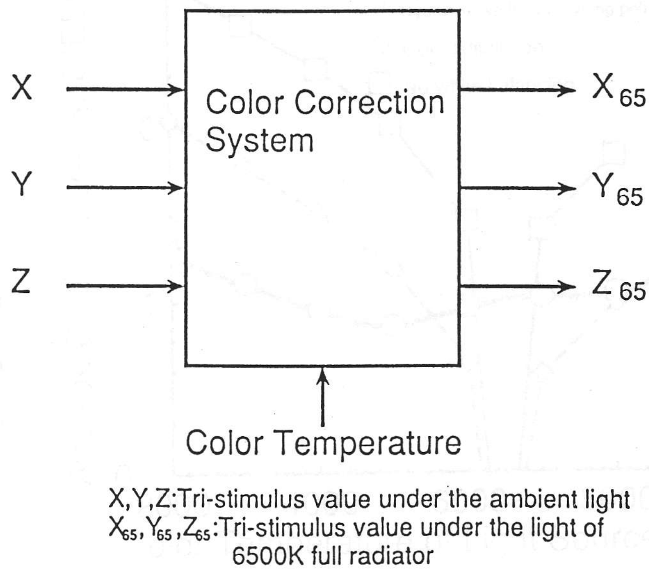

Figure 4 Colour correction system

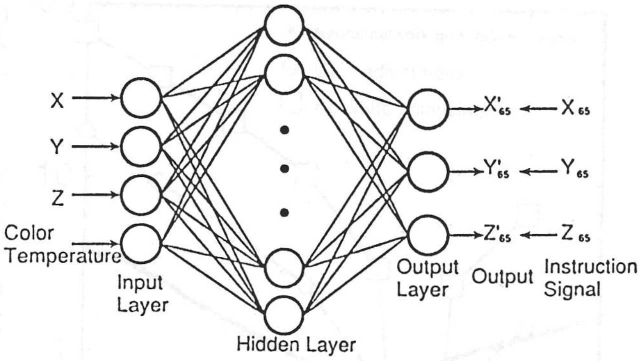

Figure 5 Neural network for white balance

source such that the RGB values were the same for the four grey colour patches of the Macbeth Color Checker.

Colour difference

The signals compensated for white balance still include colour differences. In these experiments, the differences were evaluated in the $L^*a^*b^*$ uniform colour space defined in CIE (1976) and JIS Z 8729. This colour space is designed so that colour differences showed close agreement between the numerical and perceived differences. If the tri-stimulus values obtained from the colour chart illuminated with a standard light source are X_{65}, Y_{65} and Z_{65}, and the corresponding values for standard illumination estimated from the actual lighting conditions after white balance correction are X'_{65}, Y'_{65} and Z'_{65}, the colour difference ΔE between these two colorimetric values can be found using the following equations:

$$
\begin{aligned}
L^* &= 100\cdot(Y_{65}/Y_0)^{1/3} - 16 \\
a^* &= 500\cdot[\,(X_{65}/X_0)^{1/3} - (Y_{65}/Y_0)^{1/3}] \\
b^* &= 200\cdot[\,(Y_{65}/Y_0)^{1/3} - (Z_{65}/Z_0)^{1/3}] \\
L^{*\prime} &= 100\cdot(Y'_{65}/Y_0)^{1/3} - 16 \\
a^{*\prime} &= 500\cdot[\,(X'_{65}/X_0)^{1/3} - (Y'_{65}/Y_0)^{1/3}] \\
b^{*\prime} &= 200\cdot[\,(Y'_{65}/Y_0)^{1/3} - (Z'_{65}/Z_0)^{1/3}] \\
\Delta E &= [\,(L^* - L^{*\prime})^{1/2} + (a^* - a^{*\prime})^{1/2} + (b^* - b^{*\prime})^{1/2}]^{1/2}
\end{aligned}
\qquad (4)
$$

Here, X_0, Y_0 and Z_0 are the tri-stimulus values of a fully diffuse surface.

Experimental results

In this section, we compare the performance of white balancing achieved using a neural network with that of white balancing by RGB gain adjustment, and compare the effects of both relative to a non-white-balanced signal. These comparisons were made using two groups of light sources; a total of 69 full radiators ranging from 2100–8900 K in steps of 100 K, and the A, D_{50}, D_{55}, D_{65} and D_{75} standard colorimetry light sources defined in CIE (1964) and JIS Z 8720. The latter group of light sources had colour temperatures of 2856 K, 5003 K, 5503 K and 7504 K, respectively. Their spectral characteristics are shown in *Figure 6*. As a colour table, we also used 11 patches, namely the 10 colour patches forming the color circle and a standard grey from the Mansel Book.

Figure 7 shows the average colour differences of white balance correction for each of the 24 standard colours of the Macbeth Color Checker used for training the neural network. The information actually learned by the neural network is indicated by the eight points shown in *Figure 6*, but the network was able to operate effectively over the entire range of colours, including colour temperatures that were not learned. In addition, the white balance correction obtained from the neural network resulted in a colour difference ΔE of about 1 over the range of colour temperatures from 2000–8900 K.

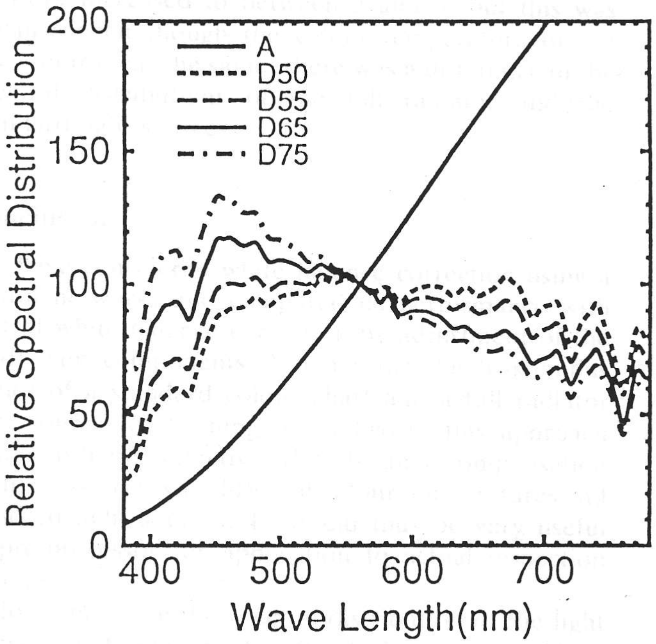

Figure 6 Relative spectral distribution of standard and supplementary lights

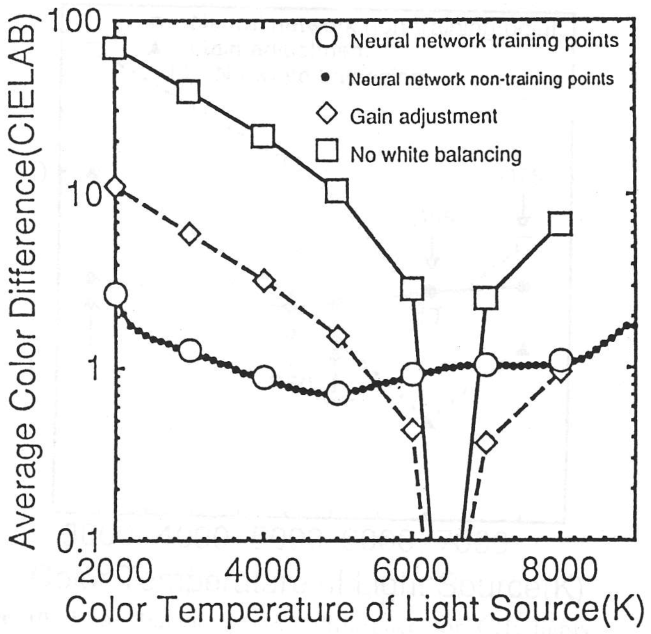

Figure 7 White balance colour difference for training patterns

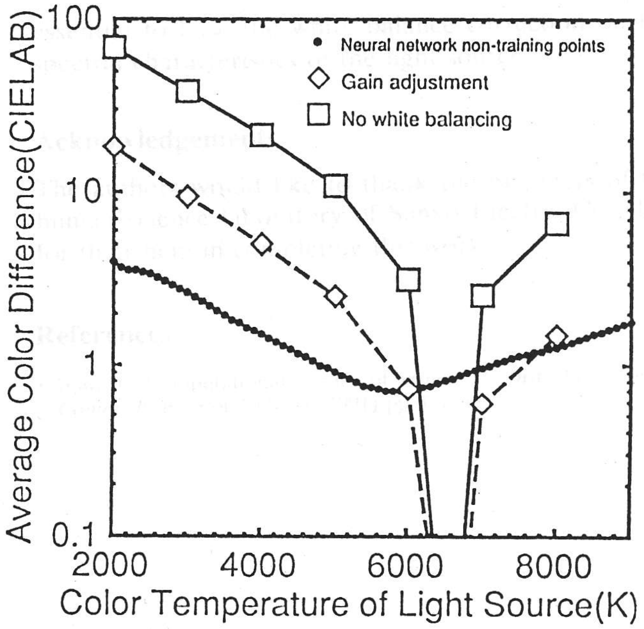

Figure 8 White balance colour difference for non-training patterns

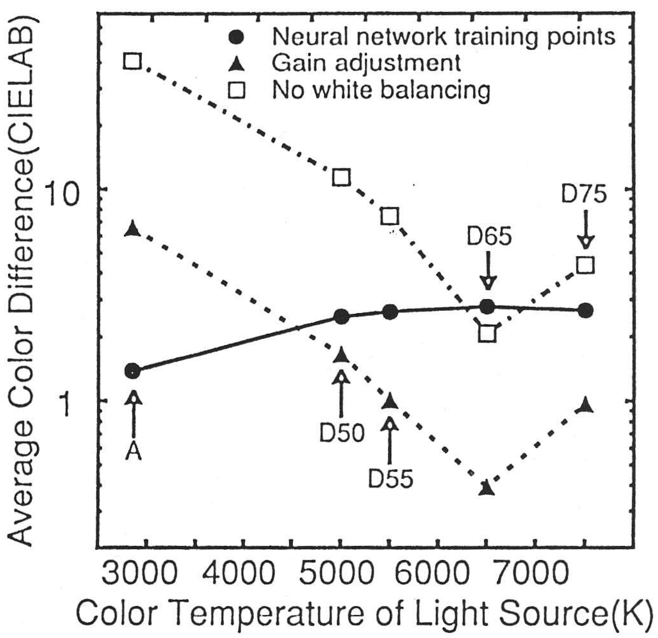

Figure 9 White balance colour difference for CIE lights (training pattern)

White balancing with RGB gain adjustment is very simple to achieve, but resulted in a satisfactory colour difference of within 3 only at temperatures above 4000 K. At lower colour temperatures, another technique must be used.

When no white balancing is performed at all, the colour difference ΔE was naturally 0 at 6500 K, but rose above 10 at colour temperatures below 5500 K. The human eye can perceive a colour difference of 5, and colour differences of 10 or more result in markedly different colours. Consequently, it is essential for the cameras used in inspection equipment to be properly adjusted for the light source.

Figure 8 shows the average colour difference of white balance correction on the eleven unlearned colours in the Mansel Book. This figure closely resembles *Figure 7*, especially in the case of the neural network balancing, which produced extremely similar results. This confirms that the neural network was capable of operating effectively even in situations not encountered during learning.

Figures 9 and *10* show the average colour differences obtained using the standard light sources defined in CIE and JIS Z 8720 to illuminate the Macbeth Color Checker and Mansel Chart, respectively. These figures demonstrate the effectiveness of white balance correction with real light sources. The average colour difference of the signals corrected with the neural network increased to between 2 and 3, but this was because even though the colour temperature of the light source was the same, there was a difference in the spectral distributions of the full radiator and the standard light sources.

Conclusion

We have considered white balance correction using a neural network, and compared its performance with that of white balance correction by adjustment of the RGB gain components. When using the tri-stimulus values of a standard colour chart and a full radiator light source for training the network, this approach results in highly effective white balance compensation for light sources with different colour temperatures and standard light sources. It should thus be very useful as pre-processor for application to actual inspection systems.

However, since the spectral distribution of the light source is not considered in this technique, to achieve white balance correction with higher performance it is

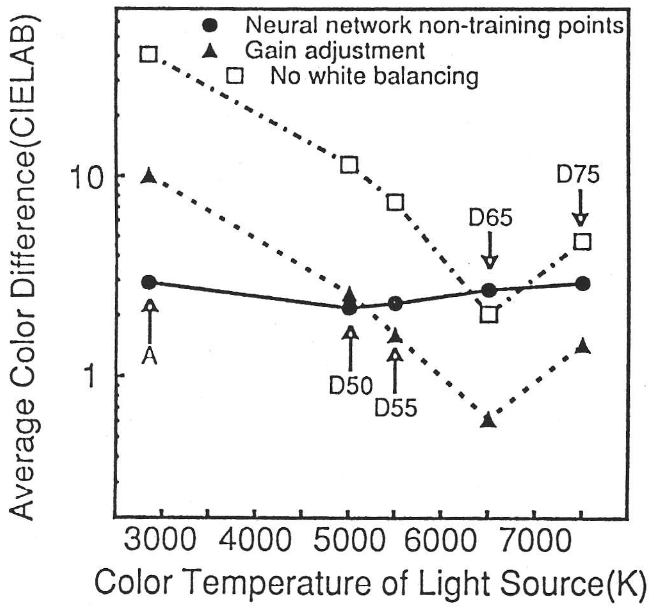

Figure 10 White balance colour difference for CIE lights (non-training pattern)

essential to base the white balance correction on the spectral characteristics of the light source.

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