

Neural Network for Color Constancy

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Abstract. Color constancy is the perceived stability of the color of objects under different illuminants. Four-layer neural network for color constancy has been developed. It has separate input channels for the test chip and for the background. Input of network was RGB receptors. Second layer consisted of color opponent cells and output have three neurons signaling x, y, Y coordinates (1931 CIE). Network was trained with the back-propagation algorithm. For training and testing we used nine illuminants with wide spectrum. Neural network was able to achieve color constancy. Input of background coordinates and nonlinearity of network have crucial influence for training.

Key words: color vision; color constancy; neural networks; computational vision.

1. Introduction

How visual system process information? There is important to solve this problem in various fields of science. One of important tasks is recognition of images. And here we need to know how visual system achieves constant perception of surrounding? For example perception of form and size of objects, distance to them, speed of movement and color does not depend on orientation of objects, distance or spectrum of illumination. But the picture on eye retina depends on those characteristics. For example perception of color of object depends on spectral distribution of reflected light from surface of object. However spectrum of reflected light depends on characteristics of object and on spectrum of illumination. Under natural conditions spectrum of illumination continually changes. It depends on surrounding also, for example in the forest and in the open lawn spectrum of illumination is very different. But regardless of that, perceived color of object does not change under those variable conditions. This phenomenon is called color constancy. Hence visual system is able to determine surface reflectance. How do it do that? There are expectations that will be possible to understand constant perception of other characteristics of objects, if we will know how is functioning perception of color constancy. Also understanding of color constancy has big practical significance in the polygraph, television, textile and other fields.

Problem of color constancy was formulated long ago (von Kries, 1905), but only in the last years this phenomenon have been intensively researched (Perceptual constancy, 1994). There are several models about perception of color constancy.

Method of adjusting receptors sensitivity. For example, if color of illumination changes from white to red, weights of red wavelength increase in the spectrum of illumination. Therefore spectrum of reflected light has more red component and receptors of long wavelength are more excited. So if we want to equalize response of receptors for red and white light, we need to decrease sensitivity of receptors for long wavelength. Such method was suggested and it is called method of adjusting von Kries coefficients (von Kries, 1905). In the beginning looked like it is possible to adjust sensitivity of all (R, G, and B) receptors independently from each other. But experiments have shown that it is not so. For example sensitivity of R receptor can be dependent on sensitivity of G and B receptors (Breive *et al.*, 1999; Wyszecki and Stiles, 1982). That reduced attractiveness of this hypothesis.

Method of evaluation changes in receptors response. There are known that visual system start to not respond to illumination if falling light on eye retina remains constant. The model has been suggested where visual system counts only spatial and time variations of illumination. This model can be realized in real neural networks as differentiation in time and space of input signal. But this model has some shortcomings. First of all, color of objects can differ, but receptors can give the same response. Color of object depends on constant illumination too. Moreover have been shown that color constancy is better when in visual field there are some objects of neutral (white-gray) color (Niuberg, 1971; McCann, 1992). It comes out that visual system can choose which color will be basic color for calculating variations. So as we see, perception of color constancy can not hold only on calculation of variations. Results obtained in experiments have shown that color perception depends on several physiological processes. Animal or human with deficiency in V4 area can separate colors but can not ensure color constancy (Zeki *et al.*, 1993). Deficiencies in other areas give color blindness.

Methods of integral perception of colors. There are some more complicated algorithms. Here color constancy is explained as integration of visual information. They suggest estimating average color in all visual field and set this color as basic, or to estimate color of illumination from shadows or highlighting.

Formal algorithms. Recently so-called formal algorithms became more popular. Because physiology of color constancy still are unknown, there are suggestions to find formal transformations that can explain how visual system ensures color constancy (McCann, 1998; Breive *et al.*, 1999; Hulbert and Poggio, 1988). In some cases there are used neurocomputers that are trained to solve mathematical equations (Hulbert, 1992). This method can help to solve some questions that arise in specific conditions. But mechanisms of color constancy are unknown. And when natural constraints change there is necessity to create new algorithms or repeat system training.

So at this time color constancy is not fully understood phenomenon. In this work we suggest to use neural network for investigation of functions of perception of color constancy. In order to do that we created neural network that is based on known structure of visual system. First neural network has been trained to achieve color constancy. Next characteristics of neural network were investigated. There have been done comparison between human perception and color transformation of neural network. Also were compared processes that are happening in visual system and in neural network.

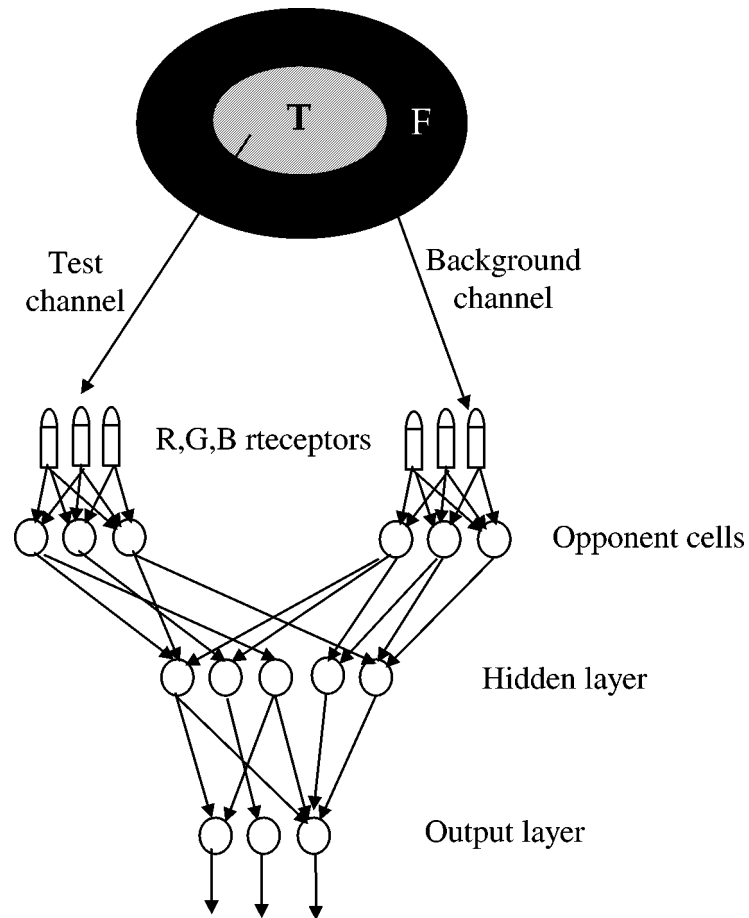


Fig. 1. Structure of neural network.

2. Methods

Structure of neural network is shown in Fig. 1. Neural network has four layers and two input channels. Each channel has three (R, G, B) receptors with different spectral sensitivity which coincide with spectral sensitivity of human receptors (Smith and Pokorny, 1975). Input signal is test stimulus surrounded with background. Receptors of one channel get signal from test stimulus and receptors of other channel get signal from background (Fig. 1). Next layer is formed with opponent cells. Those cells get inputs from receptors and have spectral sensitivity characteristics as opponent cells in human visual system (Ingling and Tsou, 1977). Neurons of hidden and output layers have sigmoid activation function. It is defined by

$$z(x) = \frac{1}{1 + \exp(-\lambda x)}, \quad (1)$$

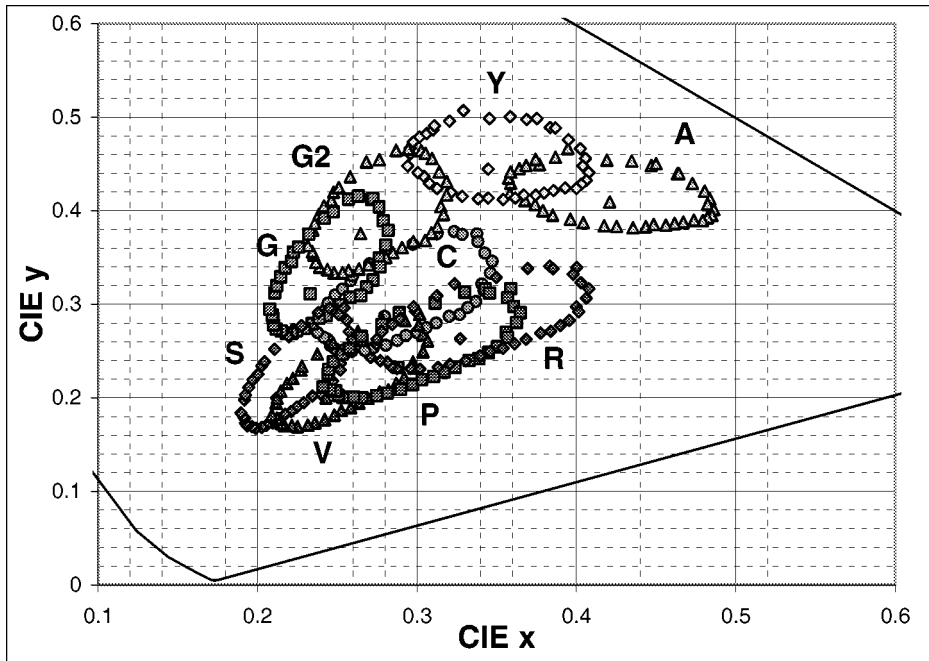


Fig. 2. Representation of Munsell samples (value 7; chroma 4) for all illuminants used in the study.

where λ is constant. In some cases activation function is linear:

$$z(x) = \lambda x + a, \quad (2)$$

where λ and a are constants.

The fourth layer consisted of three output neurons signaling x, y, L color coordinates (1931 CIE). There were possible to have color detectors in the output layer. In this case color would be described as activation of one neuron from output matrix. But we have chosen more simple output with three neurons.

Training of neural network is implemented by back propagation algorithm. Inputs for neural network was coordinates of 40 Munsell samples (value 7, chroma 8 or 4) and background (Munsell 9N sample) under various illuminants. Then input set was randomly and repeatedly forwarded for neural network input. Neural network was trained to achieve desired response, which coincides with coordinates of Munsell samples set of illuminant C. For training of neural network we used three standard illuminants: A ($x/y = 0.448/0.408$), S ($x/y = 0.232/0.232$), C ($x/y = 0.31/0.316$), and two not standard greenish (G2) ($x/y = 0.285/0.399$) and purple (P1) ($x/y = 0.326/0.263$). For testing we included four more illuminants: yellow (Y) ($x/y = 0.367/0.446$), violet (V) ($x/y = 0.273/0.232$), red (R) ($x/y = 0.367/0.29$) and blue-green (G) ($x/y = 0.251/0.343$). All illuminants have wide spectrum. Coordinates of all illuminants and Munsell samples are shown in Fig. 2.

Investigation of neural network was performed under several cases.

1. Neural network was trained with data under two illuminants (C and A), (C and S) and (C and G2).
2. Neural network was trained with data under three illuminants (C, A, S) (illuminant coordinates on (x, y) chromaticity plane reside on plankian curve), or (C, G2, P) which reside on axis orthogonal to plankian curve.
3. Neural network was trained with data under five illuminants (C, A, S, G2, P).
4. Neural network was trained in situations described in 1–3 cases, but testing was implemented with different background color. Background color was changed from 9N to color of one of Munsell sample under the same illuminant.

In all cases training was performed with two different situations: 1) neural network has input from test stimulus only; 2) neural network has input from background and from test stimulus. Training was performed under Munsell samples with chroma 8 or 4, and testing was performed with both chroma. During testing neural network gives color coordinates of Munsell samples in (x, y, L) space. Relative averaged error was estimated as ratio of a and b . Were a is Euclidean distance in (x, y) chromaticity plane between coordinates of Munsell samples of test illuminant and of coordinates produced of neural network for this sample. And b is Euclidean distance in (x, y) chromaticity plane between coordinates of Munsell samples of test illuminant and of coordinates of Munsell samples of C illuminant.

Action of neural network can be described in such way. Each sample reflects illumination $I(\lambda) = \rho(\lambda) * I_S(\lambda)$, where $I_S(\lambda)$ is spectral distribution of falling light; $\rho(\lambda)$ is surface reflectance. Physical color coordinates of object is calculated from formulae (Judd and Wyszecki, 1978; Wyszecki and Stiles, 1982):

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \int_0^{\infty} I_S(\lambda) \rho(\lambda) \begin{pmatrix} \bar{x}(\lambda) \\ \bar{y}(\lambda) \\ \bar{z}(\lambda) \end{pmatrix} d\lambda, \quad (3)$$

where $\bar{x}(\lambda)$, $\bar{y}(\lambda)$, $\bar{z}(\lambda)$ are spectral sensitivity functions of receptors. But this color space has one problem – differences between points do not correlate with subjective color differences. Therefore color spaces (x, y, L) or (u', v', L) are used instead of (X, Y, Z) . Where (u', v', L) is nonlinear transformation of (X, Y, Z) color space (Judd and Wyszecki, 1978), and (u', v', L) coordinates are chosen in such a way that distances between points correspond to subjective color differences. As we see from Eq. (3) coordinates of samples in color space depends on surface reflectance $\rho(\lambda)$, and on spectral distribution of falling light $I_S(\lambda)$. Let say that the same Munsell samples under illuminants C and test (T) will produce two sets of color coordinates $\{S_i^C\}$ and $\{S_i^T\}$, respectively. Those sets are shown in Fig. 3. After the training, neural network produces set of coordinates $\{S_{S_i}^T\}$ and this set does not coincide nor with set $\{S_i^C\}$ nor with set $\{S_i^T\}$. So, we can say that neural network performs transformation B:

$$\{S_{S_i}^T\} = B\{S_i^T\}. \quad (4)$$

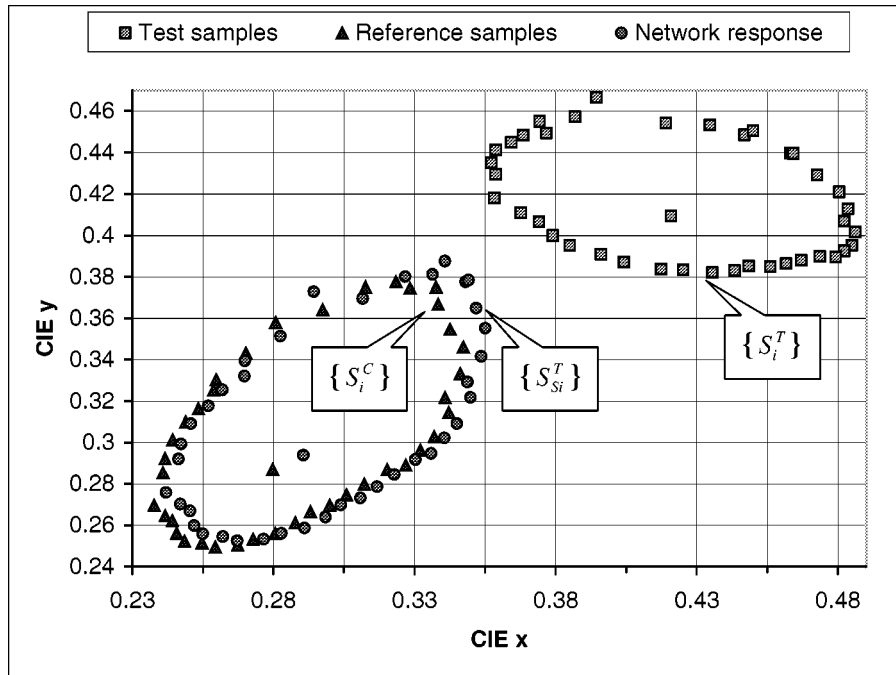


Fig. 3. $\{S_i^T\}$ is test samples. $\{S_i^C\}$ is reference samples. Response of neural network $\{S_{Si}^T\}$ does not coincide nor with test samples nor with reference samples.

We are interested in characteristics of transformation B . Does this transformation is linear, and does transformation performed by neural network is the same as visual system do?

Transformation B will be nonlinear, because activation functions of neurons in neural network are nonlinear. Does this nonlinearity is essential? In order to answer this question we investigated performance of neural net with two activation functions Eq. (1) and Eq. (2).

3. Results

1. Neural network was trained with data under two illuminants (C and A), (C and S) and (C and G2). In this case neural network restored good color coordinates only for those illuminants under which was trained. Restoration of color coordinates for other illuminants were bad. Results are presented in Fig. 4, where is shown relative error dependence on illuminant color. As we can see under training with (C and A) illuminants there are small errors for A illuminant and much bigger errors for other illuminants. The same we can say about training in two other cases (C and S) and (C and G2). Moreover for successful training neural network needs information about light reflected from background.

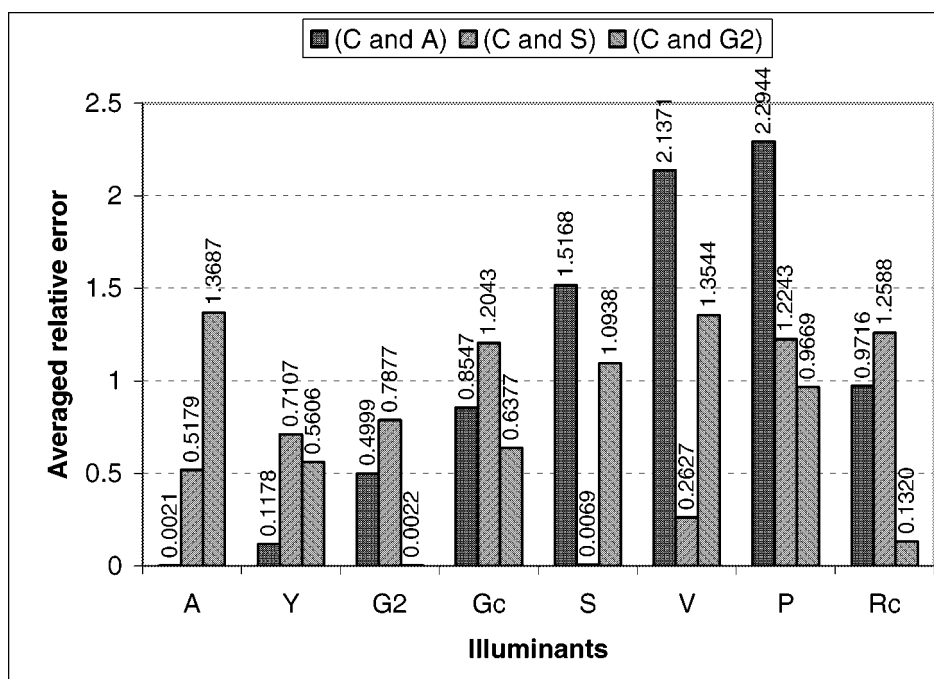


Fig. 4. Averaged relative errors of neural network testing under various illuminants. Neural network has been trained with (C and A), (C and S) and (C and G2) illuminants.

If neural network had input only from test stimulus (no background), it was not able to learn to restore color coordinates for few illuminants.

2. Neural network was trained with data under three illuminants (C, A and S) (illuminant coordinates on (x, y) color plane reside on plankian curve), or (C, G2 and P) which reside on axis orthogonal to plankian curve. Average relative errors are shown in Fig. 5. We can notice the same effect as in first training case. Small errors are only for those illuminants under which was implemented training. Illuminants that were not involved in training gives much bigger errors. Comparison of both (C, A and S) and (C, G2 and P) training shows that sum of errors of (C, G2 and P) training is smaller than of (C, A and S) training.

3. When neural network was trained with data under five illuminants (C, A, S, G2 and P), effectiveness to restore colors raised tremendously. After the training neural network was able to distinguish colors for all illuminants, doesn't matter were this illuminant presented at training or not. Values of relative average errors decreased a lot (Fig. 5), but errors of illuminants involved in training are still smaller to compare with illuminants not involved in training. Restoration results are shown in (x, y) chromaticity plane (Fig. 6). So here we have good color constancy. Effectiveness of training does not depend on saturation of samples, but errors are smaller if testing was performed with the samples of the same saturation as in training.

4. As we mentioned before, the training of neural network to achieve color constancy

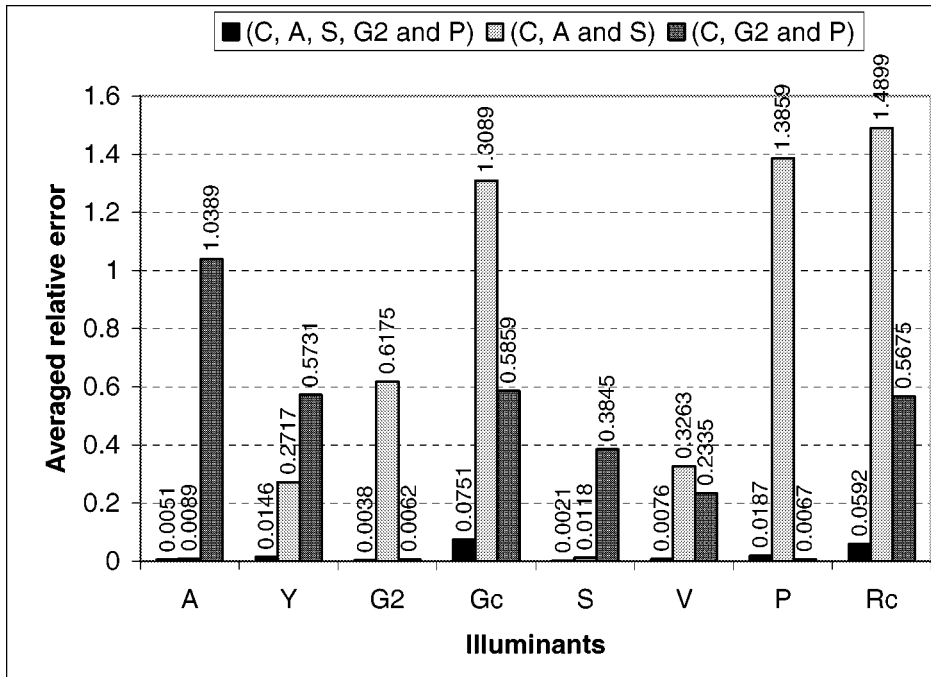


Fig. 5. Averaged relative errors of neural network testing under various illuminants. Neural network has been trained with (C, A, S, G2 and P), (C, A and S) and (C, G2 and P) illuminants.

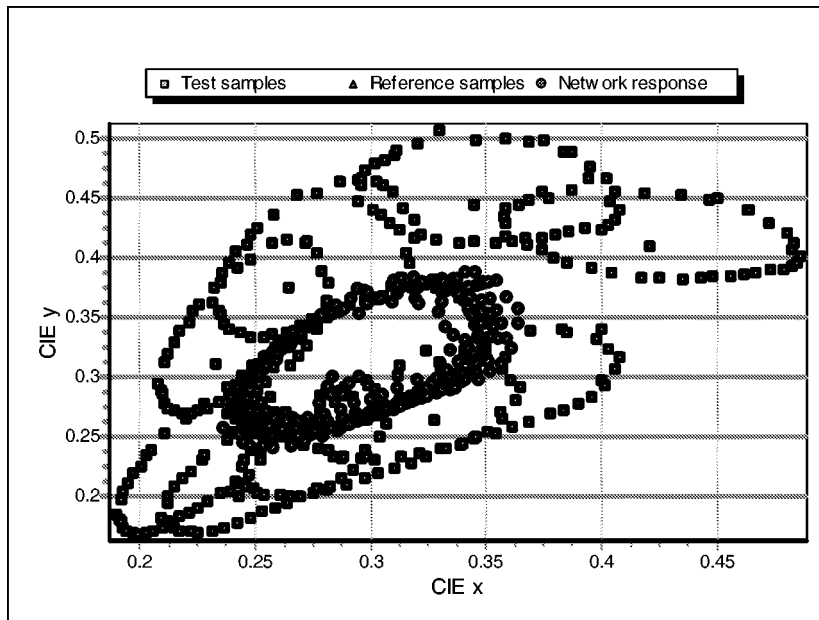


Fig. 6. Results of neural network testing with Munsell samples (value 7; chroma 4) for all used illuminants. Neural network has been trained with (C, A, S, G2 and P) illuminants.

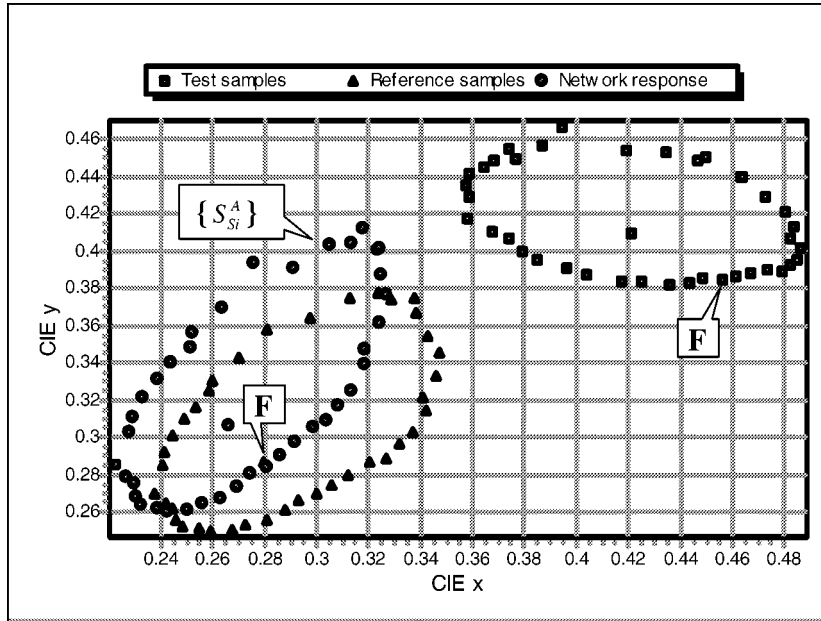


Fig. 7. Color of background was changed with color of Munsell sample F ($x/y = 0.456/0.3848$). Neural network restored color coordinates of this sample F as neutral color ($x/y = 0.281/0.284$). $\{S_{Si}^A\}$ is restoration of test samples by neural network.

failed, if there was no signal from background. To find what kind of influence background has for defining colors we did some test. Neural network trained under third condition was fed with the same samples, but color coordinates of background were changed. Background color was changed from 9N to color of one of Munsell samples. When neural network was fed with Munsell samples under illuminant A with different background, it restored different color coordinates then in case with 9N background. Locus of points $\{S_{Si}^A\}$ were shifted and color of Munsell sample (F), which was used for background, was neutral. Coordinates of sample (F) were nearby 9N sample under illuminant C (Fig. 7). So we can say that background is reference point to restore color coordinates of Munsell samples.

This conclusion was confirmed by analysis of weights of neurons. We have determined character of connection between output of opponent cells and output of output neurons. Weight matrix between opponent cells and hidden neurons was multiplied by weight matrix between hidden neurons and output neurons. (We have not counted non-linearity of neurons Eq. (1).) Those values are shown in Fig. 8. As we can see the opponent cells of different channels (T) and (F) has opposite effect on hidden neurons. In the left side of picture is shown character of (T) channel and in the right side character of (F) channel. Comes out that hidden neurons calculates difference between (F) and (T) channels.

But neurons must have nonlinear characteristics; otherwise neural network can not learn. When neuron activation function was changed to linear Eq. (2) (where $\lambda = 1$, and

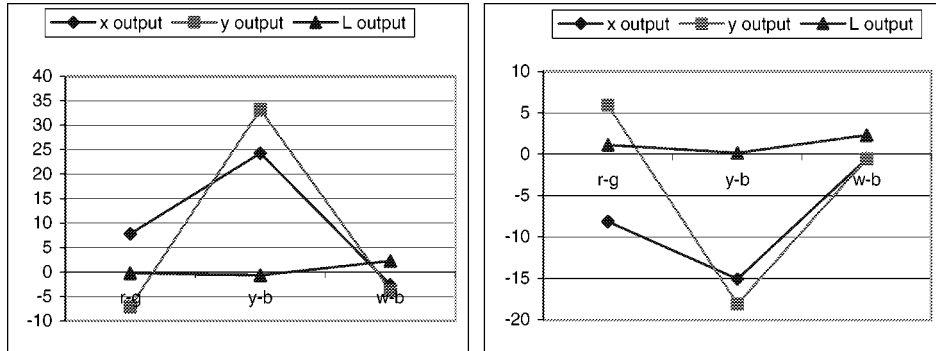


Fig. 8. Character of connection between output of opponent cells and output of output neurons. At the left side is shown for test channel, at the right side for the background channel.

$a = 0.5$), neural network was not able to learn to achieve color constancy.

There is next question, is it possible neural network describe as linear system? In order to answer it we did some calculations. We had physical coordinates of Munsell samples of test illuminant $\{S_i^T\}$ and of C illuminant $\{S_{Si}^T\}$ in the (X, Y, Z) color space. As we mention before neural network performs transformation B of color coordinates from $\{S_i^T\}$ to $\{S_{Si}^T\}$: $\{S_{Si}^T\} = B\{S_i^T\}$, where $i = 1, \dots, N$. We will check, is transformation B linear under one illuminant? Transformation is defined by 9 unknown b_{lk} ($l, k = 1, 2, 3$) coefficients. This problem does not have common solution; therefore we will find approximate solution. Let chose three points from each of $\{S_{Si}^T\}$ and $\{S_i^T\}$ sets. Then coefficients b_{lk} will be calculated: $|b_{lk}| = |s_{lk}^{TS}| * |s_{lk}^T|^{-1}$. When we will find operator B , we apply this transformation to all points $\{S_{Si}^T\} = B\{S_i^T\}$. Next we will count sum of Euclidean distances between points S_{Si}^T and BS_i^T , as $\delta = \sum_i^N |S_{Si}^T - BS_i^T|$. In common case we can make system of C_N^3 equations. We will chose such operator B that will minimize δ error. Transformation performed by optimal linear operator B is shown in Fig. 9. As we can see this linear operator performs the same transformation as neural network under one illuminant. For each illuminant we have different linear operator. So linear operator can define action performed by neural network, but this operator is different for each illuminant.

Discussions

Can we say that there is similarity between artificial neural network and human visual system? Experiments have shown that linear operator (Breive *et al.*, 1999) can define transformations performed by visual system under one illuminant. But this operator depends on illuminant color. In psychophysical experiments subjects does not have such good color constancy as neural network. Results of psychophysical experiments are shown in Fig. 10. As we can see visual system performed color transformation is such a case, that

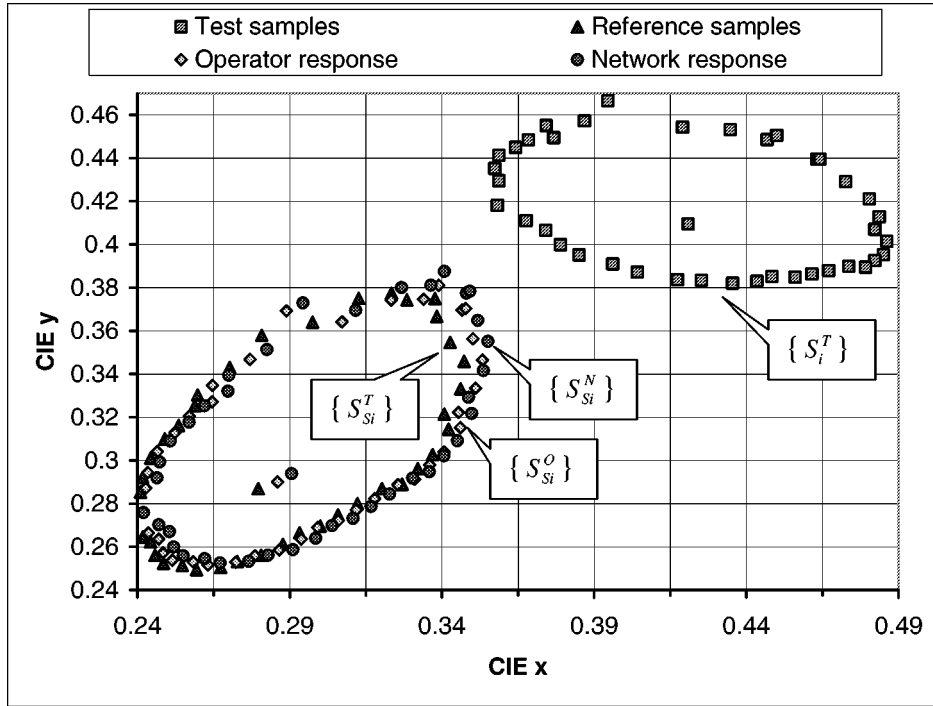


Fig. 9. Performed transformation of linear operator $\{S_{Si}^O\}$ and neural network $\{S_{Si}^N\}$. $\{S_{Si}^T\}$ is test samples under illuminant A. $\{S_{Si}^T\}$ is reference samples under illuminant C.

set of subjective color coordinates $\{S_{Si}^T\}$ is between color coordinates of Munsell samples of test illuminant $\{S_{Si}^T\}$ and Munsell samples of reference illuminant C $\{S_{Si}^C\}$. We can say that there is no color constancy, if set of coordinates $\{S_{Si}^T\}$ will coincide with set of coordinates $\{S_{Si}^T\}$, and there is full color constancy, if set of coordinates $\{S_{Si}^T\}$ will coincide with set of coordinates $\{S_{Si}^C\}$.

Experiments with neural network have shown that it behave similarly as visual system. Instead of color coordinates of test background neural network have input of average of color coordinates of test and C backgrounds (Fig. 10). Such precondition does not contradict with paradigm of psychophysical experiments. In psychophysical experiments subject was instructed to have a short look at test sample surrounded with background and illuminated with test illuminant. After that subject must choose similar color of reference sample surrounded with background and illuminated with reference C illuminant. So subject have seen background illuminated with test illuminant for short time and background illuminated with reference illuminant for long time. Because color perception changes with some inertia, it can be assumed that subjective color will be some combination of colors of test and reference illuminants. This assumption is confirmed by such an effect: color constancy is better, if presentation time of test sample is increased (Wyszecki and Stiles, 1982).

Next we tried to compare calculated operators for neural network and visual system.

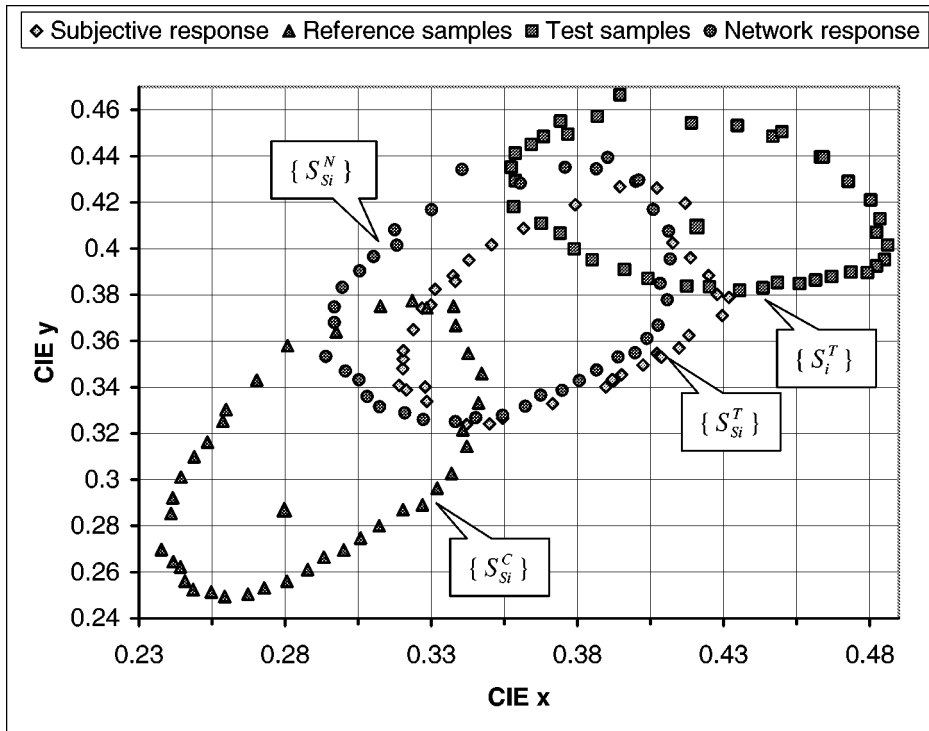


Fig. 10. Instead of color coordinates of test background neural network have input of average of color coordinates of test and C backgrounds. $\{S_{S_i}^N\}$ is response of neural network. $\{S_{S_i}^T\}$ is subjective color coordinates got in psychophysical experiment. $\{S_i^T\}$ is test samples under illuminant A. $\{S_{S_i}^C\}$ is reference samples under illuminant C.

In order to do that we have calculated eigen values and eigen vectors of operators. Eigen vectors of both operators were close to each other. When visual system is tested with green illuminant, eigen vectors have real and complex values as well. Operator for neural network has the similar characteristics.

Analysis of interaction between (T) and (F) channels gave out a conclusion, that neural network performs subtraction between signals from different channels (Fig. 8). There is a suggestion that background color is reference for calculating color of test sample (Niuberg, 1971). However analysis of neural network have shown that calculated subtraction is nonlinear function of input signals. Nonlinearity has a principal meaning – neural network can not perform learning task, if neurons have linear activation functions.

Moreover experiments show, that performing color matching task subject evaluates background color too. However, what color is accepted for background remains open. Experiments show that background is accepted as achromatic (white-black) (Niuberg, 1971; McCann, 1998). If subject perceive color objects in visual field as white-black, there is the same error in defining color for other objects as in the case with neural network when background color was other then $9N$. Let investigate two cases when in the visual field there are two stimulus: test sample and surrounding background.

Let $E_T = \{X_T, Y_T, Z_T\}$ is color vector of test sample and $E_F = \{X_F, Y_F, Z_F\}$ is color vector of surrounding background. Let linear operator O transforms X, Y, Z values to signals of opponent cells WhB, RG, Ybl so that $\{WhB, RG, YBl\}^T = O \{X, Y, Z\}^T$. Then we have difference of signals in the input of hidden neurons: $\{WhB_T - \alpha WhB_F, RG_T - \alpha RG_F, YBl_T - \alpha YBl_F\}$, where α is coefficient. This interaction means that center of coordinates is moved to point $\{\alpha WhB_F, \alpha RG_F, \alpha YBl_F\}$. When we have illuminant C, center of coordinates coincides with achromatic point. Because neural network counts color of background as achromatic (Fig. 9), it shifts center of coordinates to achromatic color. Such behavior of neural network coincides with behavior of subject. It is thought, that color defining of visual system does not depend on absolute values of receptor signals, but depend on differences between colors of stimulus and background (Nascimento and Foster, 1997).

However sometimes visual system does not have enough information from those signals to define color. In some experiments have been noticed, that absolute color of background is used for color definition too (Kulikowski, private communication, 1998). So two systems are used for color definition. One is local and another one is global. Center of coordinates of local system is related with color of background, and color of object is defined as difference of colors of stimulus and background. Global system defines color according to absolute values of receptor signals. We suppose that our neural network functions as local color system. Global color system is not counted, but it can be done easily. We need one additional independent channel that will be calculating color of background from absolute values of receptor signals. Result of this system will be dependent on color of illuminant.

Conclusions

1. The neural network is able to learn to achieve color constancy.
2. If neural network was trained using only two or three illuminants that are on one axis, it gives color constancy only for that illuminants on which were trained.
3. Neural network can be approximated with linear operator only for one test illuminant.
4. Input of background coordinates and nonlinearity of network have crucial influence for training of neural network.

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Neuronų tinklo panaudojimas spalvų konstantiškumo tyrimui

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Spalvų konstantiškumas ū tai suvokimas, kad objekto spalva išlieka nepasikeitusi kintant apšvietos spektrui. Spalvų konstantiškumui tirti buvo sukurtas keturiasluoksnis neuronų tinklas. Neuronų tinklo įėjimą sudarė du kanalai, kurių kiekvinaame yra R, G ir B receptoriai. Vienas kanalas gaudavo signalą iš testinio pavyzdėlio, o kitas ū iš fono. Antrą neuronų tinklo sluoksnį sudarė spalvinės opo-
nentinės ląstelės, trečias sluoksnis ū paslėptų neuronų sluoksnis. Ketvirtas (išėjimo) sluoksnis ū tai trys neuronai, kurių atsakai charakterizuoja spalvines koordinates x, y, L (1931 CIE). Neuronų tinklas buvo apmokytas naudojant gradientinio nusileidimo algoritmą. Apmokymui ir testavimui buvo naudojami pavyzdėliai apšviesti su 9 skirtingomis plataus spektro apšvietomis. Neuronų tinklas sugebėjo apsimokyti atlikti spalvų konstantiškumo užduotį. Fono koordinačių įėjimas ir neuronų tinklo netiesiškumas turi lemiamą reikšmę neuronų tinklo apsimokymui.