COLOUR CONSTANCY: A SIMULATION BY ARTIFICIAL NEURAL NETS

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Abstract

Colour of natural objects perceived by humans is almost independent of the illuminant, the phenomenon known as colour constancy. Its mechanisms are not yet completely understood. Calculation of colour-constancy properties is difficult due to a non-linear neuronal activity implied by current models. An alternative is offered by modelling using artificial neural networks. In our study a neural net consists of three receptor types (L, M and S); their signals are transmitted to two opponent (L/M and S/LM) and a non-opponent (Lum) units. From them signals are further conveyed to 'hidden' units, which in turn forward signals to the net output units, selective to the test colour. The net has two channels: one processing information on light reflected from a background and the other from a test. The neural net was trained to identify colour of a set of Munsell samples under various illuminants. It was then tested using original and new illuminants and an extended set of Munsell samples. We conclude that in the neural net identification of the test colour is based on calculation of colour difference between the background and the test.

Colour of natural objects perceived by humans is in large degree independent of spectral composition of illuminants. This phenomenon is known as colour constancy (D'Zmura & Lennie, 1986; Lucassen & Walraven, 1993; Troost, 1998; Breive et al, 1999; Malloney, 1999). There are a number of approaches in explaining how the problem of colour constancy may be solved by biological systems.

1. According to the von Kries coefficient model, the *gain* of three cones is changed in such a way that the cone responses are not altered by the illumination. At present it is not clear how the gain of the photoreceptors is controlled (Malloney, 1999; Wyszecki & Stiles, 2000).
2. Some authors hypothesize that *differences* in cone responses to light reflected from the background and the objects are independent of the colour of the illuminant (Yarbus, 1975; DeValois et al., 1997). However, experimental or simulation data, which could confirm or reject this hypothesis, lack (Jurkutaitis et al., 2000).
3. Recently Nascimento and Forster (1994) have shown that the *ratio* of cone responses to light reflected from the surface of different natural objects does not depend on illumination. It is, however, not clear how the ratio is utilized by the visual system to ensure colour constancy.
4. Finally, in accordance with the computational approach, a formal description of processes underlying colour constancy is hypothesized (Hulbert, 1998).

The purpose of the present work is to demonstrate that artificial neural network may be used for formal description of colour-constancy processes and, in addition, enables investigation of non-linear mechanisms underlying information processing of the object colour. Firstly we investigated how the structure of the neural net influences accuracy and speed of net training. Next, we examined potent mechanisms underlying colour constancy, as modelled by the neural net. Finally, we addressed an issue of the human colour constancy, as compared to the output of the neural net.

Method

The structure of the neural net. A multillayer perceptron with a back-propagation algorithm was used (Haykin, 1994). To simplify the study, we investigated a situation in which a single stimulus (T) is presented on a homogeneous background (B). In this case the neural net could be conventionally divided into two channels. The first, denoted by (B), processes information on light reflected from the background and the second, (T), on the light reflected from the test sample (Fig. 1). Three input units represent three receptor types (L, M, and S), whose spectral sensitivity is described by Smith and Pokorny's fundamentals (1975). An intermediate layer of the net contained of obligatory 'hidden' units. It was connected to a layer of output units, which in turn had two sub-layers of units. The first consisted of differential units (1, 2, and 3) and the second of colour selective units (C); the output signals of these latter were intended to be independent of the spectral distribution of the light source.

With regard to the intermediate layers, two net architecture variations were investigated. In one, signals from the three receptor types were transmitted via the two channels directly to the hidden units. In the other, signals from the receptors were, first, transmitted to two opponent units (L/M and S/LM) and a non-opponent achromatic (Lum) unit (cf. Ingling & Tsou, 1977), to then being transmitted to the hidden units. An activation of both hidden units and output units was described by a logistic function (Haykin, 1994).

Light sources. For training, five illuminants (A, C, S, G2 and P) were used. Power spectral distributions of two standard light sources (C) and (A) are well known. The other seven light sources had similar broad power spectral distributions. In (*x, y*) colour plane, the light of the training illuminants was located on two straight lines, approximately orthogonal to each other. For testing four additional, non-standard illuminants were used.

Stimuli. Munsell samples (value 7, chroma \2, \4, \6 and \8) served as stimuli. For training 40 Munsell samples with one chroma value (either \4, \6, or \8) were used. The trained net was tested using 160 Munsell samples with different chroma (2\, \4, \6 and \8). In Figure 2, location of Munsell samples (\6 and N7) in (*x, y*) plane under different illuminants is shown.

Training procedure. The 'training' Munsell chips on the neutral (N7) background were presented to the net under a defined illumination. The light reflected from the test samples and the background stimulated the (T) and (B) respectively. Signals generated by the receptors were further transmitted to the hidden units either directly or via opponent / non-opponent units. In turn, from the hidden unit signals were transmitted to the first sub-layer of the output units. Weights of connections between the input and hidden units and between the hidden units and output units were modified to minimize mean error $E = \frac{1}{N}\sum_{1}^{N=41}\frac{a_i}{b_i}$ in line with a back-propagation procedure using. Here a_i is a Euclidean distance between a 'veridical' and identified colour, as determined by the *output* of the differential units under presentation of

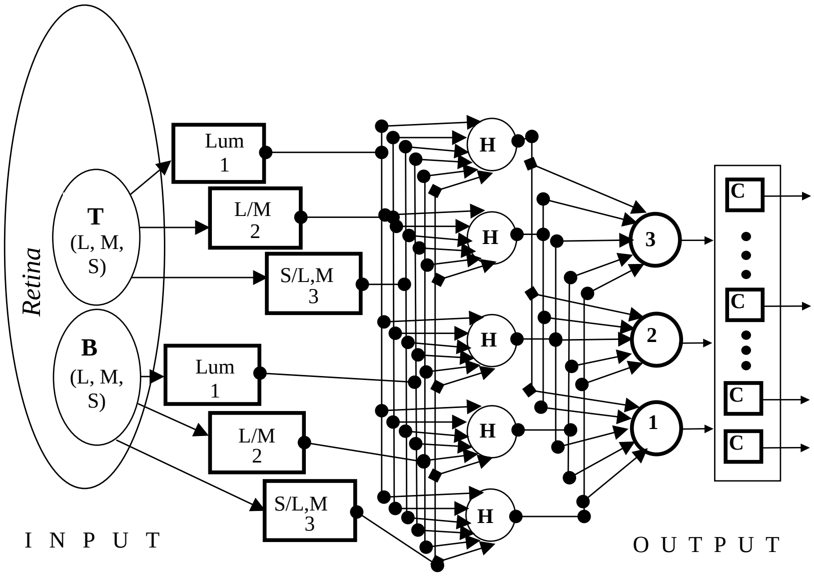

Figure 1. Structure of the neural net: **L, M, S -** receptors; **Lum** - achromatic unit, **L/M, S/LM -** opponent units; **H -** hidden units; **1, 2, 3 -** differentiation units, **C** - colour selective units.

the i^{th} Munsell sample, and b_i is a Euclidian distance between those colours, as determined by the *input* of the differential units under the standard C and given test illuminant. The training procedure was interrupted when the value of the mean error became lower than threshold value E_0. Usually duration of the training procedure was no longer than 2500 epochs, where one epoch was defined as a set of chosen samples after every illuminant was presented once.

Testing procedure followed the training. Four sets of Munsell samples (value 7, chroma \2, \4, \6 and \8) lit by one of the nine illuminants were used. The mean value of error (*E*) was measured during the testing and used to characterise quality of the training procedure.

Results and Discussion

As expected, training the net to identify colours was impossible in the absence of a background. The training of colour identification was successful only when at least four illuminants located on the two orthogonal lines (in the *x, y*-diagram) were used (Figure 2). Based on the network testing, eight sets of data were generated for the illuminants; these are depicted by letters on abscissa (Fig. 3). Ordinate (or height of a column) corresponds to the mean error at testing. For each testing illuminant, a column pattern represents three conditions with varying number (five, three, and three) of illuminants used for training. Testing illuminant is designated by corresponding letters. As Figure 3 shows, the height of the first column in each set is significantly lower than the height of the others, indicating that the

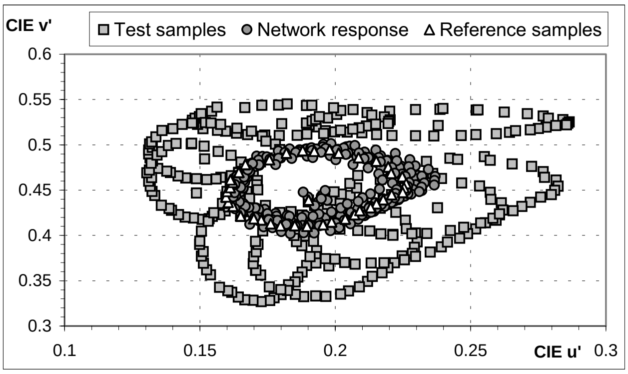

Figure 2. Identification of the object color (network response). Location of 40 Munsell samples in the CIE 1976 *u′*,*v′*-chromaticity diagram under nine illuminants.

quality of the network training was higher when five illuminants were used for training. The quality of training was also dependent upon the chroma of the used Munsell samples, specifically, the quality of training increased when more saturated samples (\8) were used (Fig. 4). The introduction of opponent and non-opponent units between the input receptors and the hidden units (viz. pre-processing of visual information) significantly shortened the length of the training session and lowered mean error (Fig. 6). Curves (Op input) and (x,y input) show changes in mean error throughout the training session with and without pre-processing of receptor signals.

A mechanism of colour constancy in the artificial neural network. Signals transmitted via the T and B channels to the output differential units had opposite signs (Figure 5). C^{s}_{ki} corresponds to the connection weight between L/M, S/LM and Lum units of the T and B channels (s=T, B) and the first sub-layer output units (i=1, 2, and 3). The neural net calculated

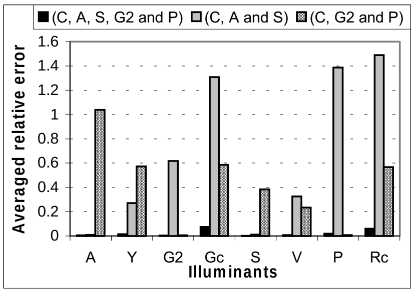

Figure 3. Dependence of error (E) upon the light sources used for training and testing of the neural net. On abscissa is the testing light source and on ordinate is the value of mean error under varying training/testing light sources.

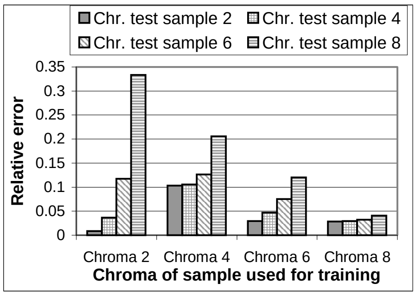

Figure 4. Dependence of error upon the chroma of samples used for training and testing. Each set of four columns corresponds to the certain chroma of samples used for training.

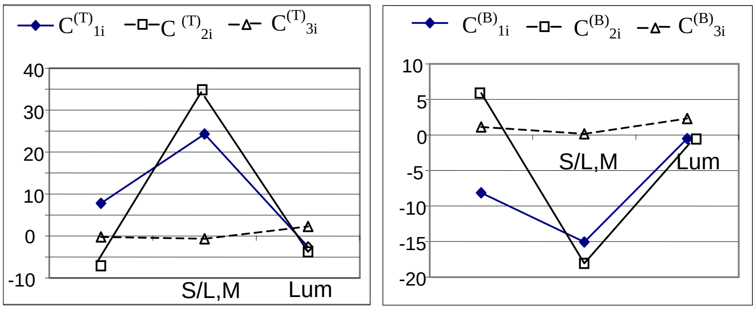

Figure 5. Connection weights between L/M, S/L,M and Lum input units of the T (***a***) and B (***b***) channels and the output differential units (1, 2, 3).

non-linear differences between responses of the T and B channels. When the net was trained to identify test colours, isoluminant with the background, there was no interaction between the achromatic (Lum) units of the T and B channels. When the background was other than neutral, the trained net could not correctly identify sample colours; in particular, the samples that were equal in their colour to the background, were identified as neutral. This is in accord with our hypothesis that the neural net calculates the differences between the colour of the background and that of the test. Similar results have been obtained earlier in psychophysical experiments (Niuberg et al, 1971; McCann, 1998). The situation became more complex when non-isoluminant samples were used for training and testing. The chromaticity identified by the trained net depended significantly on the brightness of the test sample. There were only three samples whose hue was independent of brightness. In Figure 7 an ellipse represents colour of isoluminant samples. The network was trained under three varying luminance conditions (2, 4 and 8 cd/m^2). Curved lines represent network results of identification of colour of samples of constant chromaticity under the ten luminances. As seen, the identified colour strongly depended on the luminance. An exception were samples with the dominant wavelength of about 585 and 480 nm, whose hue identification was constant (Fig. 7). It is

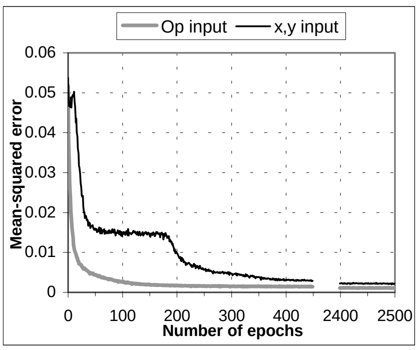

Figure 6. Mean error as a function of duration of the training (number of epochs)

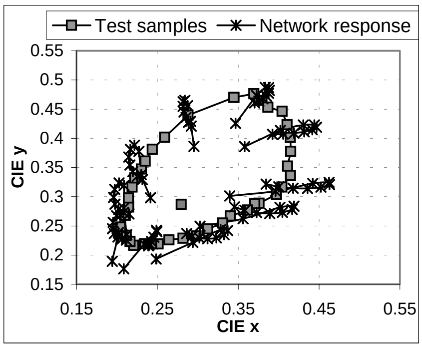

Figure 7. Effect of stimulus luminosity on identified chromaticity. Identified samples with dominant wavelength about 585, 520-540, and 480 nm hardly change hue with the change of illuminant.

worth noting, that in humans colours with approximately same wavelengths are referred to as unique hues and known to be unchangeable under variation of luminance.]

To summarize, the neural network can be easily trained to identify colour of samples presented to it on various backgrounds and under varying illuminants. The network calculates the *differences* in responses of receptor units to the light reflected from the test sample and that from the background, resulting in almost complete colour constancy. This deviates from psychophysically measured colour constancy in humans, where complete constancy is rarely observed (Lucassen & Walraven, 1993; Fairchild & Reniff, 1995; Kulikowski & Vaitkevicus, 1997**).** Such complex behavior, as modelled by the neural net, is under further investigation.

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