Dichromat's Categorical Color Perception Model

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Abstract

The purpose of this study is to get a color perception model of dichromat. We construct a color perception model of dichromat, and analyze the mechanism. Then we have prospect of find human color perception mechanism. We expect it when we understand mechanism of the color perception of the human beings by construct and analysis a dichromat's color perception model. We construct a color perception model of color defects based on the results of psychophysical experiments with optimizes the structure of neural network using genetic algorithm (GA). The neural network used in this paper is real valued flexibly connected neural network (RFCN). RFCN, the evolutionary neural network we previously proposed, is a model that can have high performance in various fields. In RFCN, the structure of the network and the parameter are optimized automatically and flexibly with GA according to tasks we give. So we can obtain the network that has desirable performance without special knowledge about the task. We developed a model that can operate similarly to dichromat ' s categorical color perception. The results showed that the obtained neural network has similar characteristics to those of dichromat ' s vision system.

Introduction

We can distinguish subtle differences between several similar colors. On the other hand, a man uses rough color category such as red or blue when he tells a color to others. This is categorical color perception that is used in the latter case. And then, there is basic color category that does not depend on sensitivity or a language. Berlin and Kay[1][2] examined more than 100 languages and concluded that eleven colors (white, red, green, yellow, blue, brown, orange, purple, pink, gray, and black) are basic color terms. Further, behavioral testing of chimpanzees has also shown similar results[3]. Franklin and Davies found evidence of categorical perception in some of these same boundaries in pre–linguistic infants and toddlers of several languages[4]. Thus, some categorical color distinctions apparently exist. From these facts, it can be considered that there may be a mechanism corresponding to their color–names in basic categorical colors in visual system. On the other hand, an object color is not only exclusively distinguish by the reflection spectrum from the surface object is but also greatly influenced by the ambient environmental conditions. We humans, however, can stably perceive an inherent an object color even reflection spectrum from the object changes according to spectrum of ambient light. This is called color constancy[5].

It can be said that categorical color the object appears under various illuminants, which is determined not only by the reflected light spectrum of the object but also by the influence of surrounding environment with color constancy. Yata *et al.* have provided a categorical color perception system which is capable to realize it[6]. That the relationship between the chromaticity of color chips under different illuminations and human categorical color perception for the color chips under the illumination can be learned by a structured neural network.

The purpose of this paper is to get a modeling system that can operate similarly to Dichromat's categorical color perception under various illuminants. We expect it when we understand mechanism of the color perception of the human beings by construct and analysis a dichromat's color perception model. We use a neural network as a model of categorical color perception. The neural network used in this paper is real valued flexibly connected neural network (RFCN)[7]. RFCN, the evolutionary neural network we previously proposed, is a model that can have high performance in various fields. In RFCN, the structure of the network and the parameter are optimized automatically and flexibly with genetic algorithm (GA) according to tasks we give. So we can obtain the network that has desirable performance without special knowledge about the task.

Real Valued Flexibly Connected Neural Network(RFCN)

We develop a model that can operate similarly to dichromat's categorical color perception using artificial neural network. The neural network as a model of categorical color perception is Real Valued Flexibly Connected Neural Network (RFCN). RFCN is a model that can have high performance in various fields. In the RFCN, every network unit is provided with unique characteristics. These characteristics include the input-output function, its parameters, and the response speed, which are optimized in the course of evolution. 1 illustrates an example of Phenotype (feed forward network structure) and Genotype (string epresenting Phenotype) in RFCN. The connection weights and unit characteristics are coded in the chromosomes. The chromosome ' s genotype is represented by a array of 0,1 genes. In RFCN, the feedback structure is restricted in genotype level. The nodes take their inputs from either the output of a previous node or from the inputs in a feed forward manner. Therefore, it is possible to straightforward execution of network , and it does not need the parameter of the number of step for feedback.

We used the following four types of input–output functions:Threshold function eq. (1), Sigmoid function eq. (2), Linear functioneq. (3), Piecewise linear functioneq. (4).

$$f(x) = \begin{cases} \alpha & (x > 0) \\ 0 & (x \leq 0) \end{cases} \tag{1}$$

$$f(x) = \frac{1}{1+\exp(-\alpha x)} \tag{2}$$

$$f(x) = \alpha x \tag{3}$$

$$f(x) = \begin{cases} 0 & (x \leq 0) \\ \alpha x & (0 < x < 1/\alpha) \\ 1 & (1/\alpha \leq x) \end{cases} \tag{4}$$

All these functions are widely used in neural networks. However, the output units in our experiments must take values in the range of 0.0 to 1.0, and therefore, only sigmoid functions

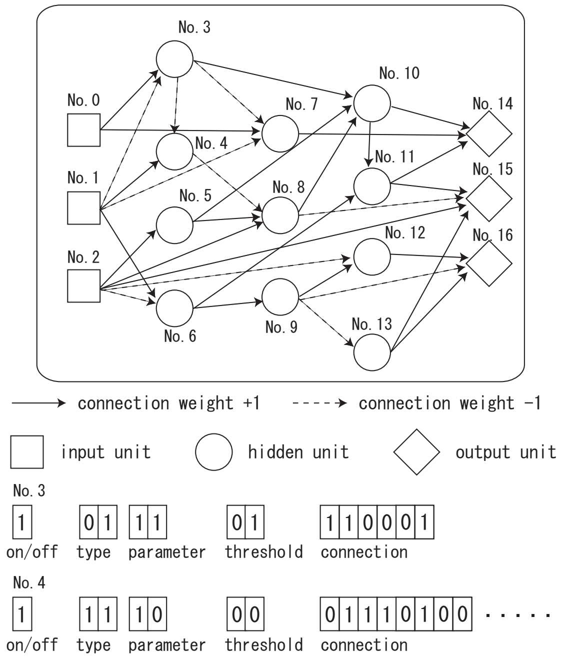

Figure 1. *An example of structure of RFCN.*

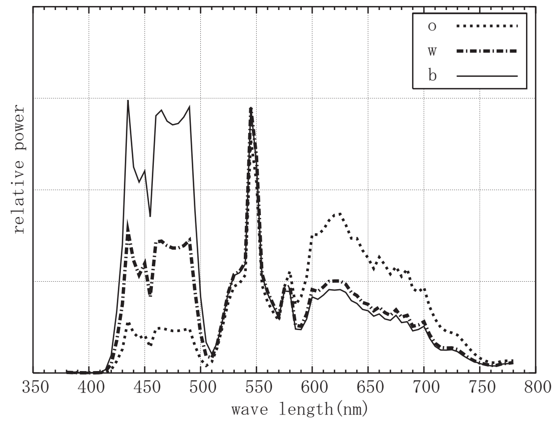

Figure 2. *Spectral distributions of illuminant.*

and piecewise linear functions were used for the output units. In addition, we used four values of the parameter α, namely, 0.25, 0.5, 1.0, and 2.0: that is, the same function could produce a different response depending on the parameter. As a result, a network involved units with various responses, thus allowing more complicated processing even though the connection weights are restricted to the simple values +1, 0, and -1.

Every unit of the RFCN operates in a different way because it is provided with a different response speed. In our experiments, we use only two kinds of units in terms of response speed, fast units and slow units.

A structure of the network and the parameter are optimized automatically and flexibly with Genetic Algorithm (GA) according to tasks we give. When the crossover operator is applied, the crossover points are selected at random in the chromosome ' s rows and columns so as to divide a chromosome into four parts. The blocks thus generated are then interchanged to implement crossover. For each individual, the number of hidden units is decremented or incremented at a mutation rate. In the case of decrementing, the units to be removed are selected at random, and the corresponding gene loci are deleted. In the case of incrementing, additional genes are inserted outside the chromosome. Gene mutations occur at the gene level at a mutation rate. The bits of mutated genes are inverted.

Experiments and Results

We can obtain the network that has desirable performance without special knowledge about the task. The inputs of the RFCN are cone visual cells ' responses (L,S) or (M,S) which are calculated from chromaticity of a illumination and that of a sample color under the illumination. The outputs of the network represent the categorical color–name of the sample color.

Training Data

Training data used by the neural network will be explained. A training data set used in the embodiment is prepared by a psychophysical experiment by which categorical color perception is measured under three types of illuminants. This experiment is carried out by displaying 424 OSA color chips (an example of color samples) one by one on a board of N5 (in Munsell color system) gray under a illuminant by an LCD projector from the ceiling. Table 1 shows correlated color temperature and CIE (1931) xy chromaticity of the three types of the illuminants used for this experiment. Further, Fig. 2 shows spectral distribution of these illuminants.

Appearance of a color of displayed stimulus is measured by a categorical color naming method. According to this method, among eleven basic categorical colors, one color–name which represents the best appearance of each color chip under each illuminant is answered.

The test subjects are four as S1, S2, S3, and S4. S1 and S2 are protanopes. S3 and S4 are deuteranopes.

A number of examinees are four, two sessions are experimented with the each illuminants, naming 424 kinds of color chips in one session, and then 3 illuminants $\times$ 2 times $=$ 6 sessions are experimented. Accordingly, training data of 3 illuminants $\times$ 424 $=$ 1272 sets are prepared.

Each of the input data for the test color component were converted from luminance *Lum* and CIE(1931)*xy* chromaticity coordinate (x, y) of the OSA color chips measured under each of the illuminants[8]. Cone responses were calculated based on Judd modification of CIE color–matching function for the CIE 1931 Standard Colorimetric Observer[9]. Namely, conversion to (L, M, S) cone response values according to eq. (5).

$$\begin{pmatrix} L \\ M \\ S \end{pmatrix} = \begin{pmatrix} 0.15514 & 0.54312 & -0.03286 \\ -0.15514 & 0.45684 & 0.03286 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} \quad (5)$$

The input data for the illuminant component are similarly converted from the measured value Lum and (x, y) of the illuminant to (L, M, S) cone response values. The obtained (L, M, S) are used for input data by normalizing between $[0, 1]$.

For training data for outputs, real numbers are used, which are obtained by normalizing to $[0, 1]$ a color–name using a rate which shows how many times a certain basic–color–name is used for appearance of a certain color chip out of answers of each parson $\times$ 2 sessions obtained as a result of the experiment. By making the network learn such a training data, the RFCN learns a mapping performed by Dichromat from the LS or MS cone responses to the names of basic categorical colors as a computation task.

CIE(1931)xy–chromaticity of illuminants.

Illuminant	Correlated color xy–Chromaticity
o (3000K)	(0.439, 0.410)
w (6500K)	(0.313, 0.332)
b (25000K)	(0.255, 0.252)

The parameters used in the experiments.

Parameter	Value
Generation alternation model	MGG*
The number of generations	300000
Population size	150
Child size	30
Uniform crossover rate P_c	0.5
Crossover rate	0.7
Mutation rate P_m	0.001
The maximum number of units	50

* Minimal Generation Gap[10]

Experimental setup

We use a RFCN as a model for each subject. The inputs of the networks are cone visual cells ' responses (L,S) or (M,S) which are calculated from chromaticity of a illumination and that of a sample color under the illumination. The outputs of the networks represent the categorical color–name of the sample color. The parameters used in experiments are given in Table 2.

The fitness F of each individual was calculated as follows:

$$F = 10 * \frac{n}{N} + (1 - \frac{e}{N}) \qquad (6)$$

where n is a times of output correct color name, N is a number of data set, and e is a value of error (distance between output values and training data).

Experimental results

The learning result will be explained. The color–names which answered by S2 shows in Fig. 3,5,6. Output of network for S2 shows in Fig. 4,7,8 A point is drawn on a specific coordinate on $j-g$ plane in OSA space by a color–name of subject's answeror output of network.

To confirm that learning was corrected, the same input values as ones of the learning data set are inputted to the obtained neural network and the output is checked. Table.3 shows matching rate between outputs of the trained network and the training data. We see from table.3 that the training has been finished successfully.

CONCLUSION

To get a modeling system that can operate similarly to Dichromat's categorical color perception, the relationship between the chromaticity of color chips under different illuminations and the color chips' categorical color perception under the illumination that is the product of a categorical color naming experiment was learned by RFCN. Experimental results show that the obtained RFCN has the similar input-output response to those of Dichromat's vision. The relationship between chromaticity of color chips under different illuminations and categorical color–names for the Dichromats under the illuminations were learned with RFCN.

The number of correct answer for each subject using RFCN.

	o	w	b	total
S1	74.3%	88.0%	80.7%	81.0%
S2	73.1%	75.7%	75.9%	74.9%
S3	71.7%	75.5%	82.8%	76.7%
S4	69.8%	81.6%	78.1%	76.5%

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Author Biography

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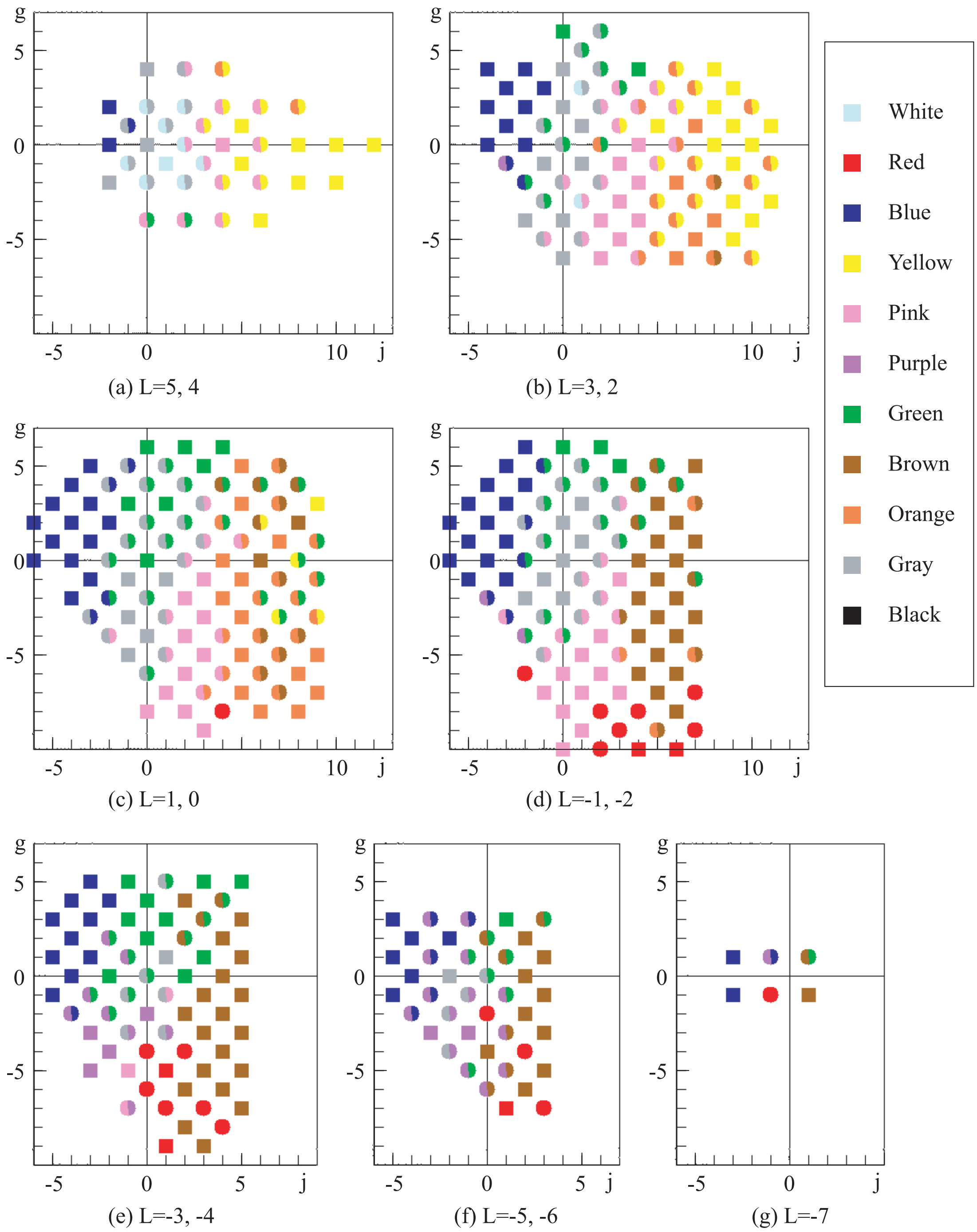

Figure 3. *Distribution of color–names under the illuminant w which answered by S2.*

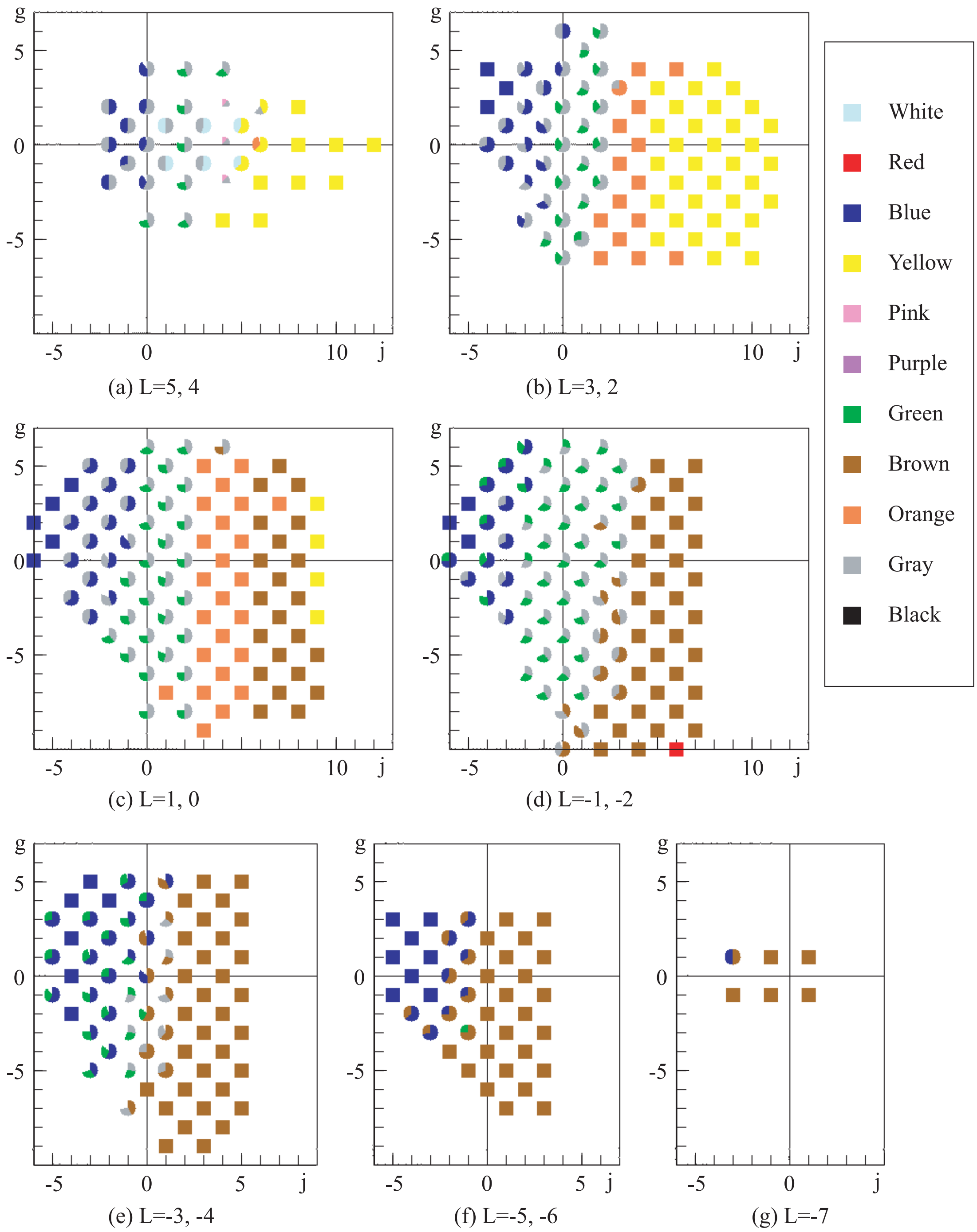

Figure 4. *Output of network for S2 with the illuminant w.*

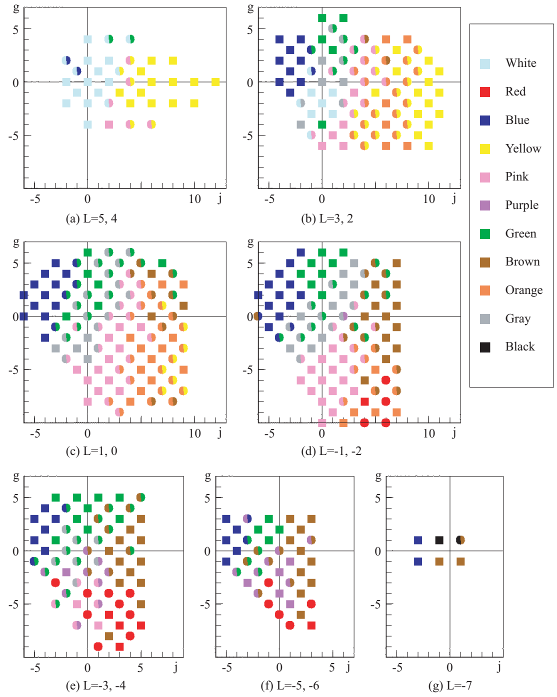

Figure 5. *Distribution of color–names under the illuminant o which answered by S2.*

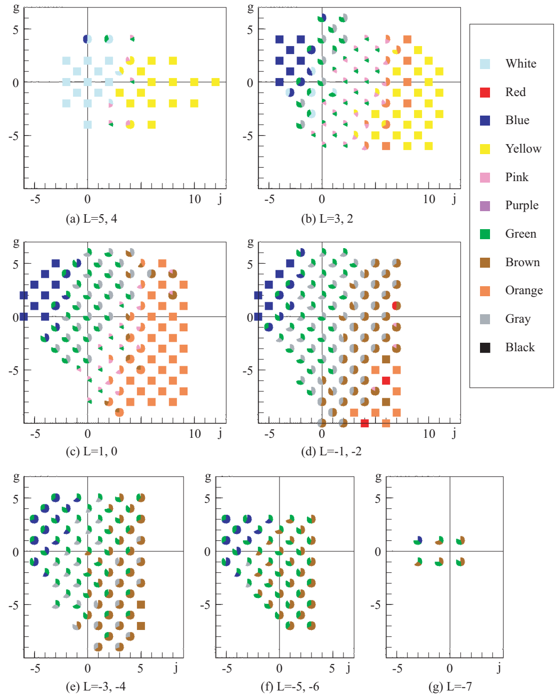

Figure 7. *Output of network for S2 with the illuminant o.*

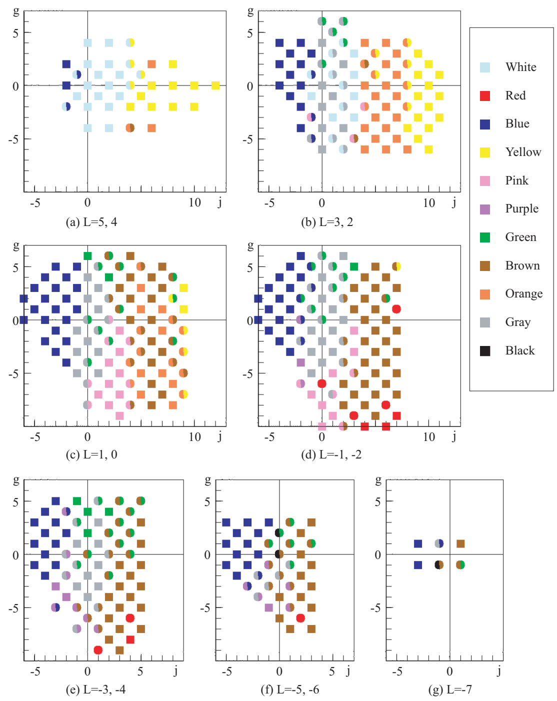

Figure 6. *Distribution of color–names under the illuminant b which answered by S2.*

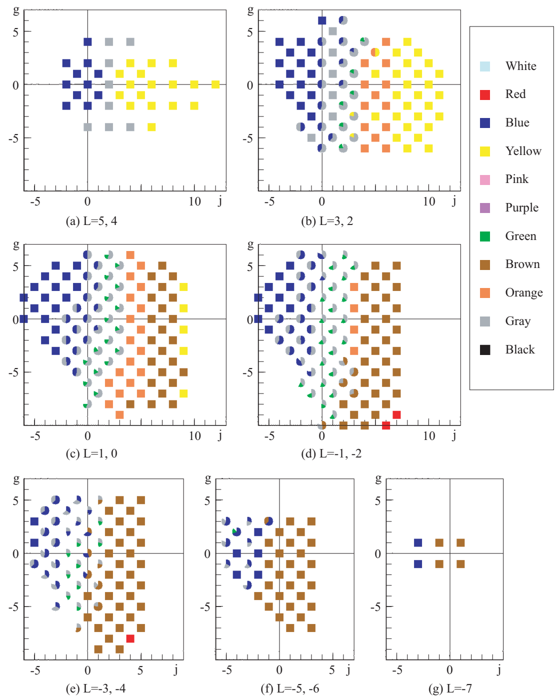

Figure 8. *Output of network for S2 with the illuminant b.*