Analysis of Relationships Between Mood and Color for Different Musical Preferences

Chang Bae Moon, HyunSoo Kim, Hyun Ah Lee, Byeong Man Kim*

Department of Computer Software Engineering, Kumoh National Institute of Technology, Korea

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Abstract: We investigated the relationship between mood and color according to musical preference. Volunteers were requested to select the mood evoked by music and the color associated with a mood word, and the color distributions and mood distributions were then analyzed with two-way ANOVA using Minitab. The results of the analysis indicated that mood and color were differently distributed, depending on the music genre presented and the musical preference of the listener. © 2013 Wiley Periodicals, Inc. Col Res Appl, 39, 413–423, 2014; Published Online 23 April 2013 in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/col.21806

Key words: mood of music; color distribution of mood; mood distribution of genre; color distribution of genre

INTRODUCTION

In modern societies, individual activities have increased at the expense of group activities. A representative individual activity is listening to music. Listening to music with colored illumination can provide a deeper appreciation of the music than listening alone. The problem arises of how to determine the color of the illumination that matches the music. Several methods have been developed for this purpose; however, regardless of the selection process, some listeners may disagree with the color of the illumination chosen for a particular musical piece. In this study, we analyzed the relationship between color and music according to the musical preference of the listener.

To analyze the relationship between color and music, we collected mood data for music samples and color data for mood words from recruited volunteers. The mood evoked by each of 281 samples of music was selected from the mood model, expressed as 12 adjectives, in a questionnaire completed in an online environment. The same adjective was then presented to the same person, who was asked to state the color evoked by that adjective. The volunteers were classified according to their musical preferences and the input data were used to analyze the mood distributions and color distributions evoked by different musical genres according to these musical preferences. Using two-way analysis of variance (ANOVA), we found that the mood evoked by specific music and the color attributed to that particular mood were differently distributed according to the listener's musical preference.

RELATED STUDIES

Representative mood models include the Russell model,[1] Hevner model,[2] and Thayer model.[3] Because the Russell and Hevner model use adjectives to describe emotion, ambiguity can arise when the adjectives have duplicate meanings. The Thayer model addresses the problem of ambiguity by using two models, dividing the music-evoked mood into the vector values arousal and valence in a two-dimensional (2D) model. Arousal expresses the strength of the stimulation felt by the listener in response to a piece of music and valence expresses the stability of the sound.

Lee *et al*.[4] detected the mood evoked by music, by automatically determining a representative section of a piece of music, extracting the features of the representative section, and determining the mood of the music with support vector regression. Analytical studies of musical structure use methods that search sections of music for tone changes or instrumental changes[5,6]; structural analysis methods determine semantic regions such as

*Correspondence to: Byeong Man Kim (e-mail: bmkim@kumoh.ac.kr).

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introduction, verse, chorus, ending, and so forth, by use of the music onset representing the time tempo of the song[7]; other methods are based on clustering similarity matrices between feature vectors[8,9]; others look for repetitious structures of similar melodies[10]; and others analyze the virtual musical chord order, or measure the regularity and similarity.[11–13]

Diverse studies have investigated the association between music and color.[14–16] Barbiere *et al*.[14] asked subjects to assign a color to a musical mood, using two types of mood ("happy" or "sad") and 11 basic colors. They showed that brighter colors were usually associated with happy songs and gray was usually assigned to sad songs. Bresin[15] asked subjects to rate how well each of eight colors and their three nuances corresponded to each of 12 musical performances expressing different emotions. They showed that different hues were associated with different emotions. They also showed that dark colors were associated with music of minor tonality and light colors with music of major tonality. Odbert *et al*.[16] investigated the moods of music using the Hevner model and also examined the "color" of the music. By analyzing the relationship between the mood of the music and the colors suggested by that music, they showed that subjects who disagree on the mood of the music also tended to disagree on the color of that music. Their results were very similar to those obtained when the subjects were asked to name the color that best suited the corresponding mood words.

Several researchers have investigated the relationship between color and mood.[17–21] Manav[17] defined the relationship between color and mood using adjectival mood words. The subjects selected the words that most closely matched each of 41 colors, from 30 adjectival words, including vivid, boring, cold, warm, exciting, fearful, mysterious, peaceful, and relaxing. Manav also analyzed 10 colors in relation to education level according to age and sex, and identified the sensitive colors that are best suited to bedrooms, bathrooms, and children's rooms. Valdez and Mehrabian[19] investigated the relationship between mood and color using the pleasure–arousal–dominance (PAD) model of emotion and provided PAD-value prediction equations based on the parameters hue, saturation, and brightness. They demonstrated strong and highly predictable relationships between brightness/saturation and emotional reactions, whereas the relationship between hue and emotion was very weak. Ou *et al*.[21] showed that color preference can be determined by three color emotion scales ("clean–dirty," "tense–relaxed," and "heavy–light") and that the "clean–dirty" scale was dominant over the other two. They also showed that color preference can be defined by the three attributes of a color (hue, lightness, and chroma), and that the most disliked color occurs at a hue angle of 105° with a chroma of 31.

DATA ON MUSIC-EVOKED MOOD AND MOOD-EVOKED COLOR

To analyze the mood evoked by music and the color associated with this mood, we extracted a representative section from a piece of music. This extracted section was presented to each volunteer to evoke a mood; the mood word selected was then presented to the same volunteer, who selected the color evoked by that word. The collected mood data were then analyzed and verified with two-way ANOVA.

Extracting a Representative Section of Sound

For the analysis of musical structure, we used a method based on the state sequence,[12] where the window size was three times the hop size and the hop size was equal to the beat length of the music (typically 300–400 ms), estimated with a beat-tracking algorithm. These were used to extract the primary sound features. We used a fixed frame with a length of 1.2 s and a hop size of 300 ms.

As the primary sound features of a frame, audio spectrum projection features were used, which is a part of the MPEG-7 standard. The audio spectrum envelope (ASE) was initially computed with the short-time Fourier transform and was then normalized. The principal components analysis (PCA) basis was then derived from the training data. Finally, the projection of the spectrum was obtained by multiplying the normalized ASE by the extracted basis. In our experiments, we used the first 20 PCA components; however, the information on the energy difference in each frame disappeared because the ASE values were normalized. Therefore, we extracted an additional sound feature, the L2 norm of the power spectrum, finally yielding 21D feature vectors, which were used as the inputs for a hidden Markov model to obtain the virtual code (or timbre-type) sequence.

After the virtual code sequence was extracted, a soft k-means clustering method based on a histogram[15] was used to separate the music into segments. To separate it into M segments, the data histograms were generated based on the virtual code sequence in a window of size W, while the window was moved over the virtual code sequence. The segment sequence was then defined, as shown in Fig. 1, by assigning the label of the cluster to which each data histogram belonged.

After defining the segments, each segment was separated into 12 s units from the starting point of the segment, according to the method of Kim and Brian.[5] All segments of less than 12 s were ignored. Each separate unit was called a "music segment." Among the music segments, one source was selected from the "intro" section, one source from the "outro" section, and the source with the highest energy value was selected, as calculated with Eq. (1). The selected music segments were used as the sound sources with which to collect the mood information on the music.

$$\varepsilon_x=\sum_{-\infty}^{\infty} x(n)x(n)^*=\sum_{-\infty}^{\infty}|x(n)|^2 \tag{1}$$

where ε_x is the energy of a signal x, $x(n)$ is the sample of signal x at time n, and $x(n)^*$ is the pair complex number of $x(n)$.

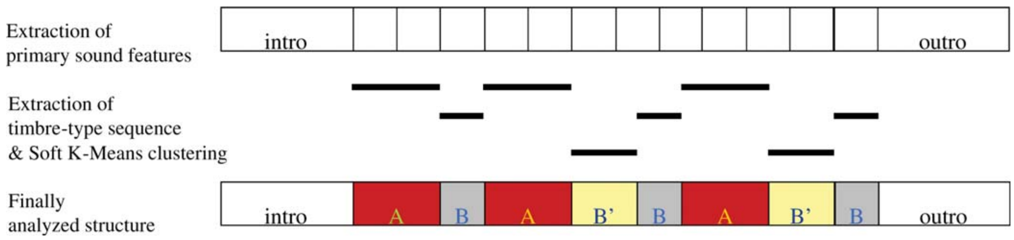


FIG. 1. Structural analysis of similar sections based on clustering methods.

Collecting the Mood of the Sound Source and the Color of the Mood Words

To gather the data on mood and color, we recruited volunteers who wanted to participate in our experiments. Each volunteer was asked to provide information about his/her sex, age, job, and musical preference. To determine the musical preferences of the volunteers, we provided 18 genres from common music websites.

We collected the data on the moods evoked by the music segments and the color evoked by each mood word from 189 volunteers between 10 am and 5 pm on 3 days in a room with dark glass on the eastern wall. The sound source was composed of 281 music segments, which were extracted from 101 songs, each with a playing time of 12 s. The music segments were combined into six groups and more than one group was played to each volunteer. A headset was provided to suppress any external noise.

The data were collected with the following process: (1) each volunteer submitted their demographic information (e.g., preferred music genre, age, job, listening time per week, etc.) to our mood collecting system; (2) when the volunteer logged in, the mood collecting system [accessed via a user interface (UI), Fig. 2] provided a sample of a music segment to him/her; (3) the volunteer listened to the music segment and then recorded his/her response to it through the UI; (4) when the input was complete, the input datum was saved to the database of the mood collecting system and the next randomly selected music segment was played to the volunteer.

For the web UI that contained the questionnaire about mood, the 2D Thayer model was used (as shown in Fig. 2). The volunteer was able to select 1–3 moods for each music segment with corresponding graded scores. The total of score for each segment should be 5. The selection of two conflicting moods at the same time, such as "angry" and "peaceful," was not permitted. Therefore, if the participant entered a mood from quadrant 1, he/she could not also enter a mood from quadrant 3; however, a volunteer could choose moods from neighboring quadrants, so that when a volunteer selected moods from quadrant 1, he/she could also select moods from quadrants 2 or 4.

The "Etc" field in Fig. 2 is intended for use when a volunteer feels a mood other than the 12 moods suggested, but it was not used in our experiment. Volunteers might not understand the meanings of words or may feel burdened by the need to interpret them if only English words were given. Therefore, the first available Korean synonyms for the English words, as listed in an internet dictionary, were also given.

To collect the color data for the mood words, our system provided the word in the upper part of the mood color collection UI, as shown in Fig. 3. The volunteers were able to see the word provided, and then selected the color that they considered matched the word. The preview in the lower area of Fig. 3 was used by the volunteers to confirm the selected color. The color table above the preview is the default color table of Java of which the default color space is sRGB.[22] sRGB is a standard RGB color space created cooperatively by HP and Microsoft for use on monitors, printers, and the Internet.[23] When a volunteer clicked the SAVE button after selecting a color, the RGB value of the color was saved and another mood word was provided by the server. In studies about basic color terms, colors from the Munsell system have been widely used by many researchers,[18,20,24] but, in this article, the Java color set is used because we consider an LED lighting system reflecting mood of music as the main application of our study and so we need to generate colors by mixing red, green, and blue primaries. As mentioned in Ref. 26, the Munsell system is based on visual perception and not on paint mixing or the mathematical formulas of computer color palettes.

FIG. 2. Input screen for music mood.

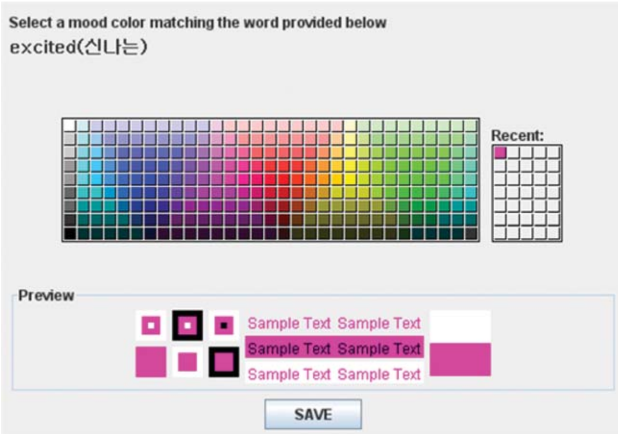


FIG. 3. Mood color collection UI.

Table I shows the musical preferences of the volunteers. To prevent biased results arising from the analysis of small groups, we used only the five preference groups (Rock, Pop, Rap/Hip-Hop, Dance Music, and Ballads) that had more than 10 adherents. The age range of the volunteers is from 20 to 30, among which 95% is undergraduate students and others are graduate students or school staff.

RELATIONSHIP BETWEEN MOOD AND COLOR

To define the relationship between color and the mood evoked by music, we first defined the representative mood evoked by a music segment and derived the mood distribution of the preference group for each genre. We also determined the color distribution of the preference group for each genre.

Representative Mood of the Music Segment

Because several listeners may designate different moods for one music segment, the representative mood for that segment must be defined. For this, the total score for each mood was first calculated as follows:

$$\mathrm{ed}_i^s=\sum_{u=1}^{n}\mathrm{data}_{u,i}^s,\ \begin{cases} i=1,2,3,\ldots,12 \\ n:\text{number of volunteers}\end{cases} \quad (2)$$

where ed_i^s is the total score of the volunteers for the ith mood for a given music segment s, and $\mathrm{data}_{u,i}^s$ is the score of the ith mood of volunteer u for s. The mood index, i, ranges from 1 to 12 and corresponds to pleased, happy, excited, …, relaxed, reading counterclockwise from 1, as shown in Fig. 4.

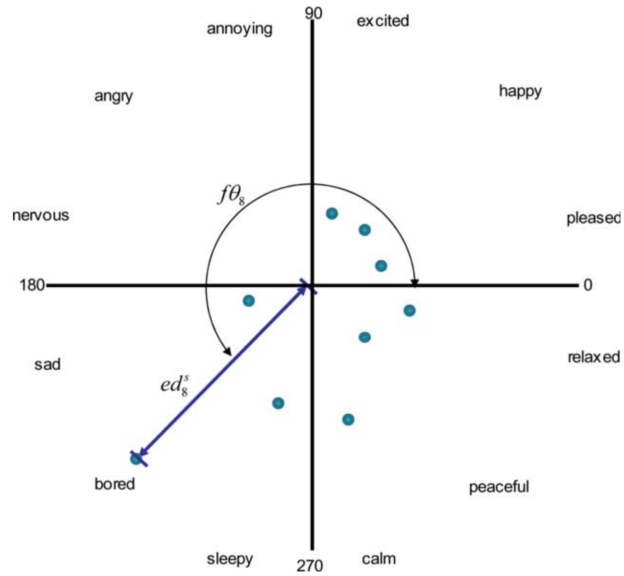


FIG. 4. Vector composition of ed_i.

After ed_i^s was determined for each mood, it was converted to a coordinate value in AV (Arousal and Valence) space with Eq. (3), in which $f\theta_i=f\theta_{i-1}+30(2\le i\le 12)$ and $f\theta_1$ is 15°.

$$x_i=\mathrm{ed}_i^s\times\cos(f\theta_i)\quad\text{and}\quad y_i=\mathrm{ed}_i^s\times\sin(f\theta_i)\quad (3)$$

When (x_i, y_i) was determined for each mood, we calculated their central coordinates and selected the representative mood by finding the mood axis that was closest to the center obtained. Thus, angle $c\theta$ was acquired as *atan* $(\bar{x},\bar{y})$ on the basis of Eq. (4), and then Eq. (5) was used to calculate the index *NI* of the closest mood.

$$\bar{x}=\frac{1}{12}\sum_{i=1}^{12}x_i\qquad \bar{y}=\frac{1}{12}\sum_{i=1}^{12}y_i\quad (4)$$

$$\mathrm{NI}=\arg\min\{d\theta_i\}\text{where},d\theta_i=|f\theta_i-c\theta|,i=1,2,3,\ldots,11,12\quad (5)$$

Music Mood Distributions of the Preference Groups for Each Genre

Because the music segments were presented at random when the mood data were collected, the number of

TABLE I. Distribution of the music preferences of the participants.

Preference group	Count	Preference group	Count	Preference group	Count
Ballads	66	Modern simple pop	4	Crossover	1
Dance music	31	Indie	4	Alternative	0
Rap/hip-hop	21	Rhythm and blues	3	Brit pop	0
Pop	15	Electronic	2	Brass	0
Rock	14	World music	2	Etc.	9
New age	5	Punk	1	Not selected	4
Jazz	5	Country/folk	1	Total	189

TABLE II. Mood distribution by the Dance Music preference group for the Rock Folk genre.

Mood	Music no.	Music genre	Total respondents	Rate of music contribution (R) (%)	Rate of mood contribution (w) (%)
Happy	RF.1	Rock folk	5	14	68
	RF.2	Rock folk	3	8	
	RF.3	Rock folk	7	19	
	RF.4	Rock folk	4	11	
	RF.5	Rock folk	6	16	
Sad	RF.6	Rock folk	4	11	11
Excited	RF.7	Rock folk	2	5	22
	RF.8	Rock folk	5	14	
	RF.9	Rock folk	1	3	
Total			37	100	100

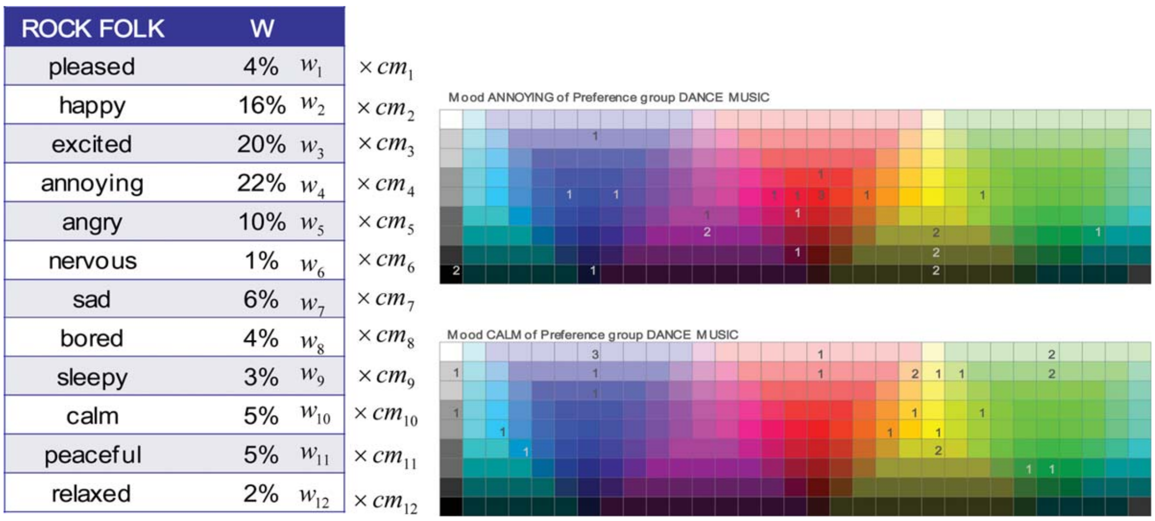


FIG. 5. Example of the calculation process for the mood color matrix of a preference group for a genre.

volunteers responding to each music segment was not same. Thus, when calculating the mood distribution, we added the rate of contribution of a music segment to accommodate those cases with more or fewer volunteers, using Eq. (6).

$$R^p_{g,k} = \frac{\text{Number of People}^p_{g,k}}{Total\ of\ People^p_g} \tag{6}$$

where $R^p_{g,k}$ is the rate of contribution of genre g and preference group p to the kth music segment; $\text{Number of People}^p_{g,k}$ is the number of respondents to the kth music segment from genre g, and $\text{Number of People}^p_g$ is the number of respondents to any segment from genre g, on which at least one member of preference group p provided a rating.

The mood distribution was obtained by calculating the contribution rate for each mood with Eq. (7), where $w^p_{g,i}$ is the contribution rate of genre g and preference group p to the ith mood, and I is a set of music segments from genre g on which at least one member of preference group p provided a rating. Table II shows the mood distribution of preference group "Dance Music" for genre

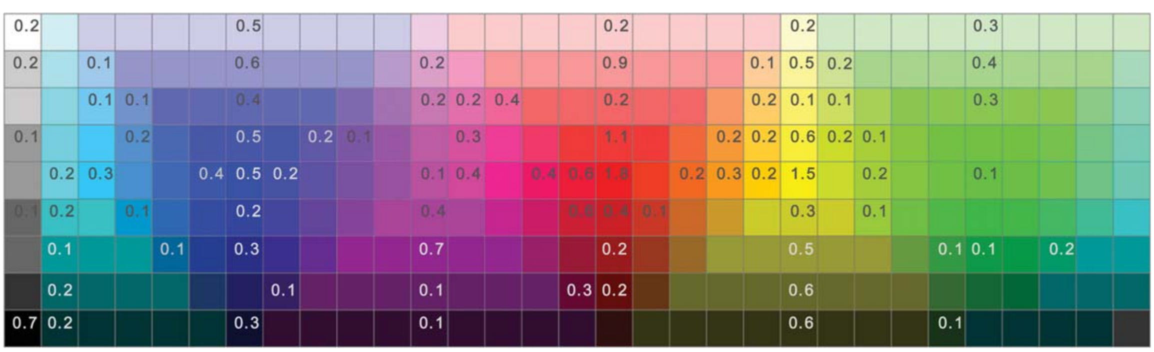
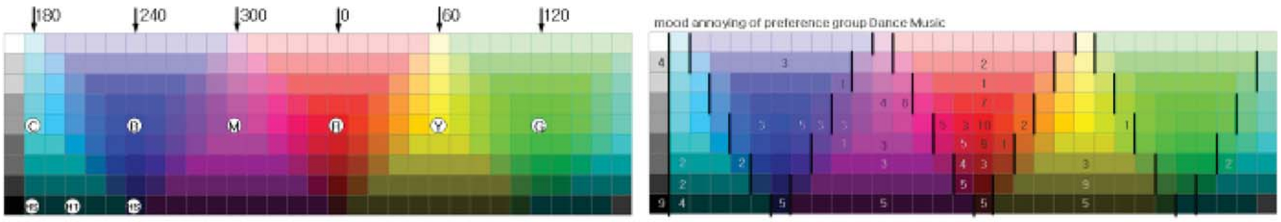
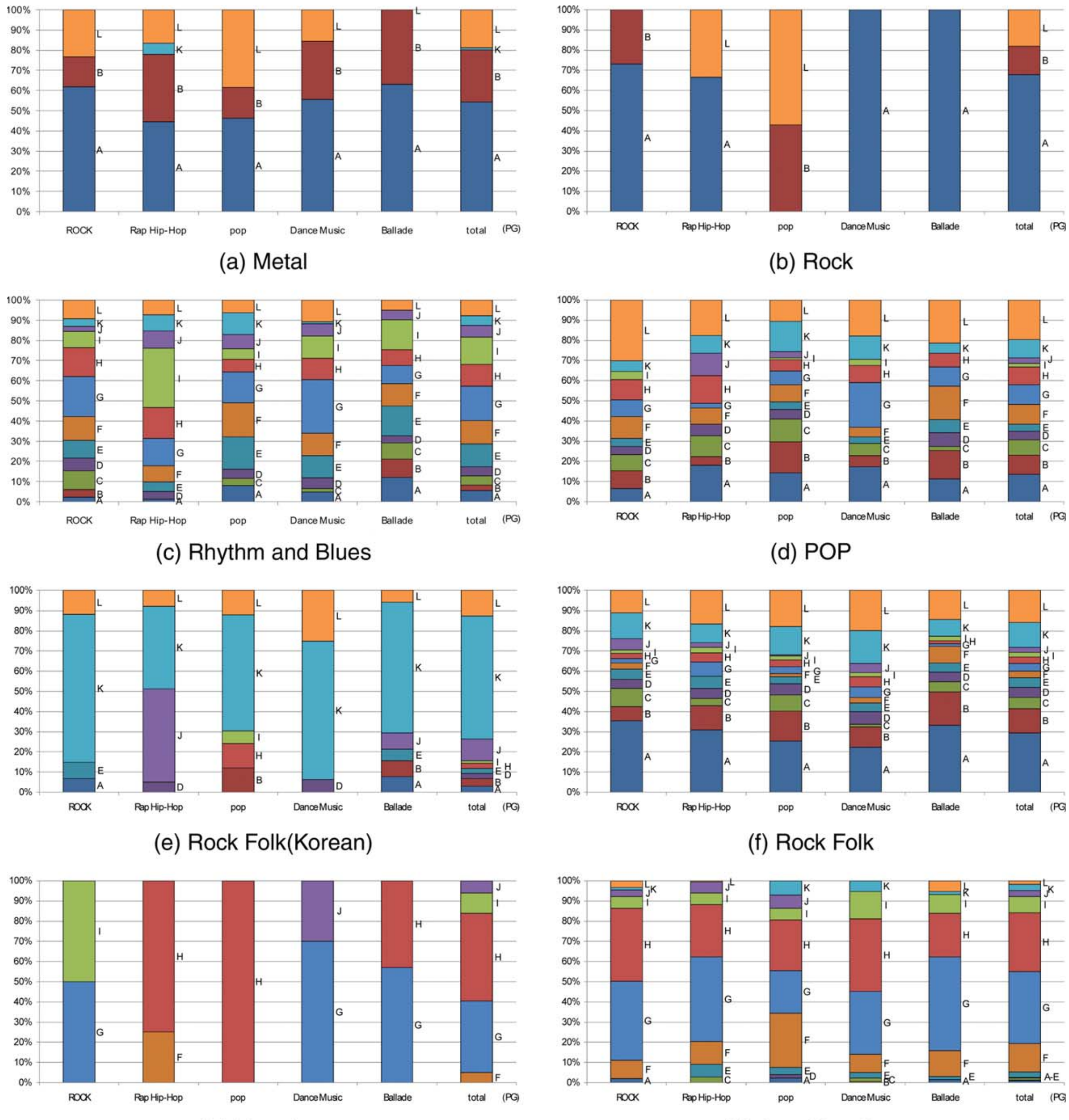


FIG. 6. Mood color matrix of preference group "Dance Music" for genre "Rock Folk."



(a) Positions and *hue* values of the basic colors (b) Areas covered by the basic colors

FIG. 7. Positions and areas of the basic colors. (a) Positions and hue values of the basic colors (b) Areas covered by the basic colors.



(a) Metal (b) Rock

(c) Rhythm and Blues (d) POP

(e) Rock Folk(Korean) (f) Rock Folk

(g) New Age (h) Jazz New Age

FIG. 8. Mood distribution of music genre for each preference group (A: annoying, B: angry, C: nervous, D: sad, E: bored, F: sleepy, G: calm, H: peaceful, I: relaxed, J: pleased, K: happy, L: excited, PG: preference group).

TABLE III. Results of two-way ANOVA of mood according to the music genre.

DV	Arousal			Valence		
IV	PG	MG	PG*MG	PG	MG	PG*MG
df	4	7	28	4	7	28
F_0	153.22	3252.14	629.21	64.79	1183.51	267.84
P value	0.000	0.000	0.000	0.000	0.000	0.000

PG: preferred genre; MG: music genre; PG*MG: interaction; DV: dependent variable; IV: independent variable.

"Rock Folk." The distributions for all combinations of preference groups and music genres are shown graphically in Fig. 8.

$$w^p_{g,i} = \sum_{k \in I} R^p_{g,k} \tag{7}$$

Mood Color Distributions of the Preference Groups for Each Genre

The color distribution of preference group p for the ith mood defined by cm_i^p can be obtained by counting the colors that the volunteers selected for the ith mood. Two color maps corresponding to the moods "annoying" and "calm" are illustrated in Fig. 5. Each color map can be directly converted to 9×31 matrices $\mathrm{cm}_4^{\text{Dance Music}}$ and $\mathrm{cm}_{10}^{\text{Dance Music}}$, respectively, whose elements are the numbers of volunteers selecting the color. This was then used to

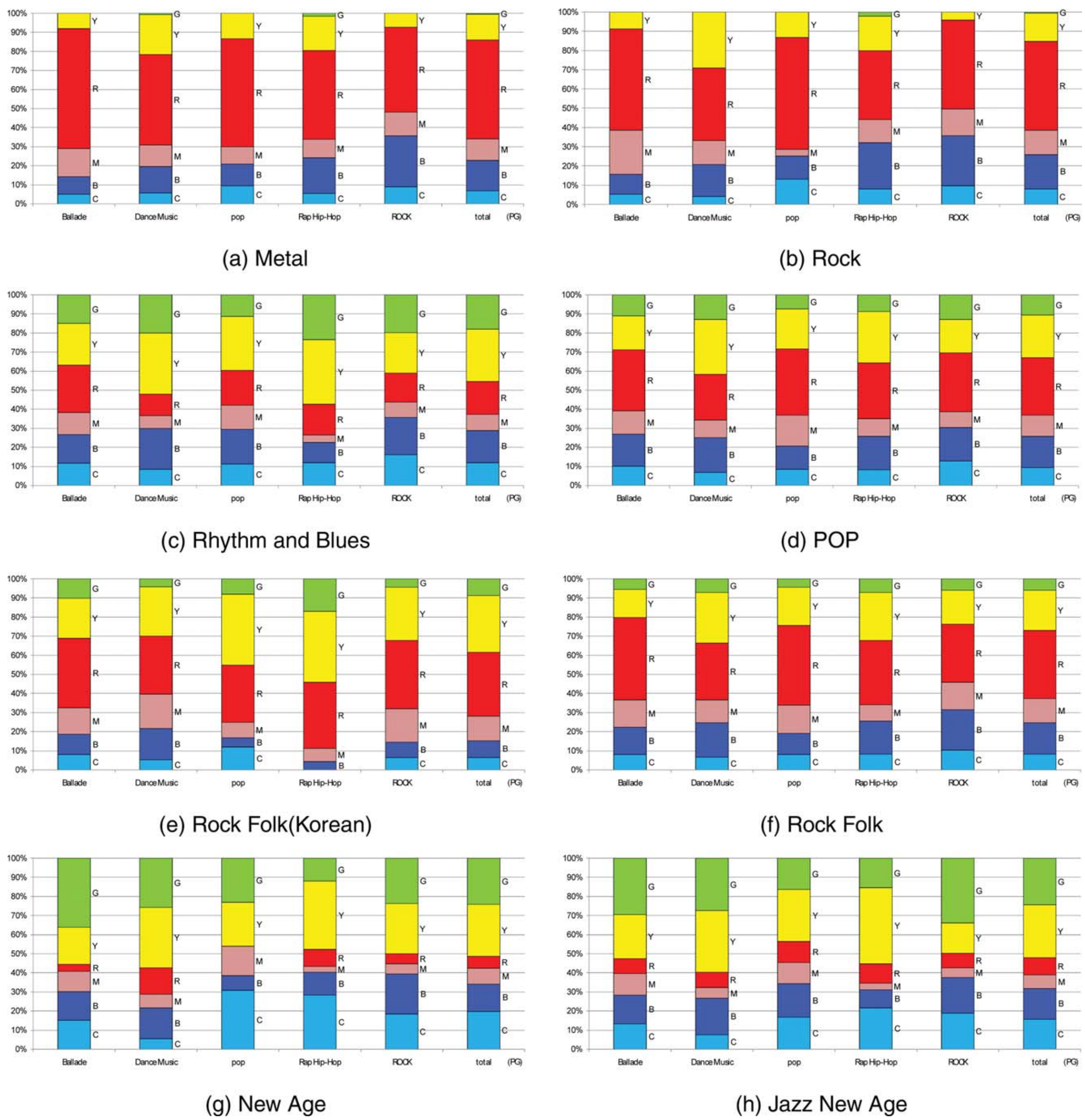


FIG. 9. Comparison of color (hue) distribution of music genre for preference group (R: red, G: green, B: blue, C: cyan, M: magenta, Y: yellow, PG: preference group).

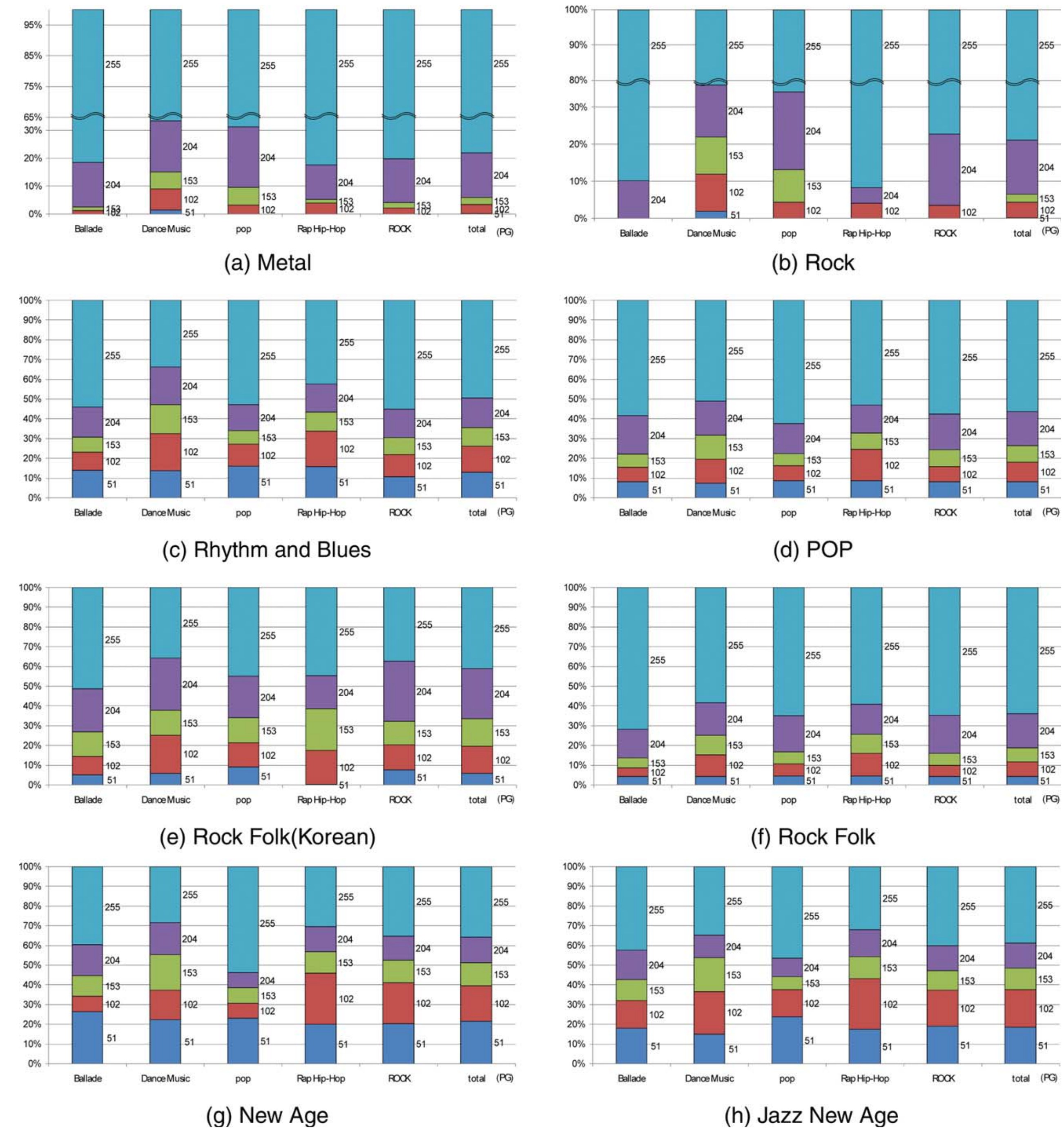


FIG. 10. Comparison of color (saturation) distribution of music genre for preference group (PG: preference group).

calculate the mood color distributions of the preference groups for each genre. If the matrix corresponding to the ith mood color map of preference group p is cm_i^p and the contribution rate of genre g and preference group p for the ith mood is $w_{g,i}^p$, then the color matrix of preference group p for genre g denoted by MGCM_g^p can be obtained with Eq. (8).

$$\mathrm{MGCM}_g^p=\sum_{i=1}^{n} w_{g,i}^p \times \mathrm{cm}_i^p \tag{8}$$

where p is the preference group, g is the genre of the sound source, i in the index of mood, and n (= 12) is the number of moods.

Figure 5 illustrates pictorially the calculation process for the mood color matrix of the preference group "Dance Music" for the genre "Rock Folk." Because space is limited, only two color maps corresponding to $\mathrm{cm}_4^{\text{Dance Music}}$ and $\mathrm{cm}_{10}^{\text{Dance Music}}$ are presented. The final color map of preference group "Dance Music" for genre "Rock Folk," $\mathrm{MGCM}_{\text{Rock Folk}}^{\text{Dance Music}}$, is shown in Fig. 6.

To simplify the analysis of the color distribution for each genre, we used six basic colors instead of 279 colors: red, green, blue, cyan, magenta, and yellow. The positions and *hue* values of these basic colors are shown in Fig. 7(a) and the areas covered by the basic colors in

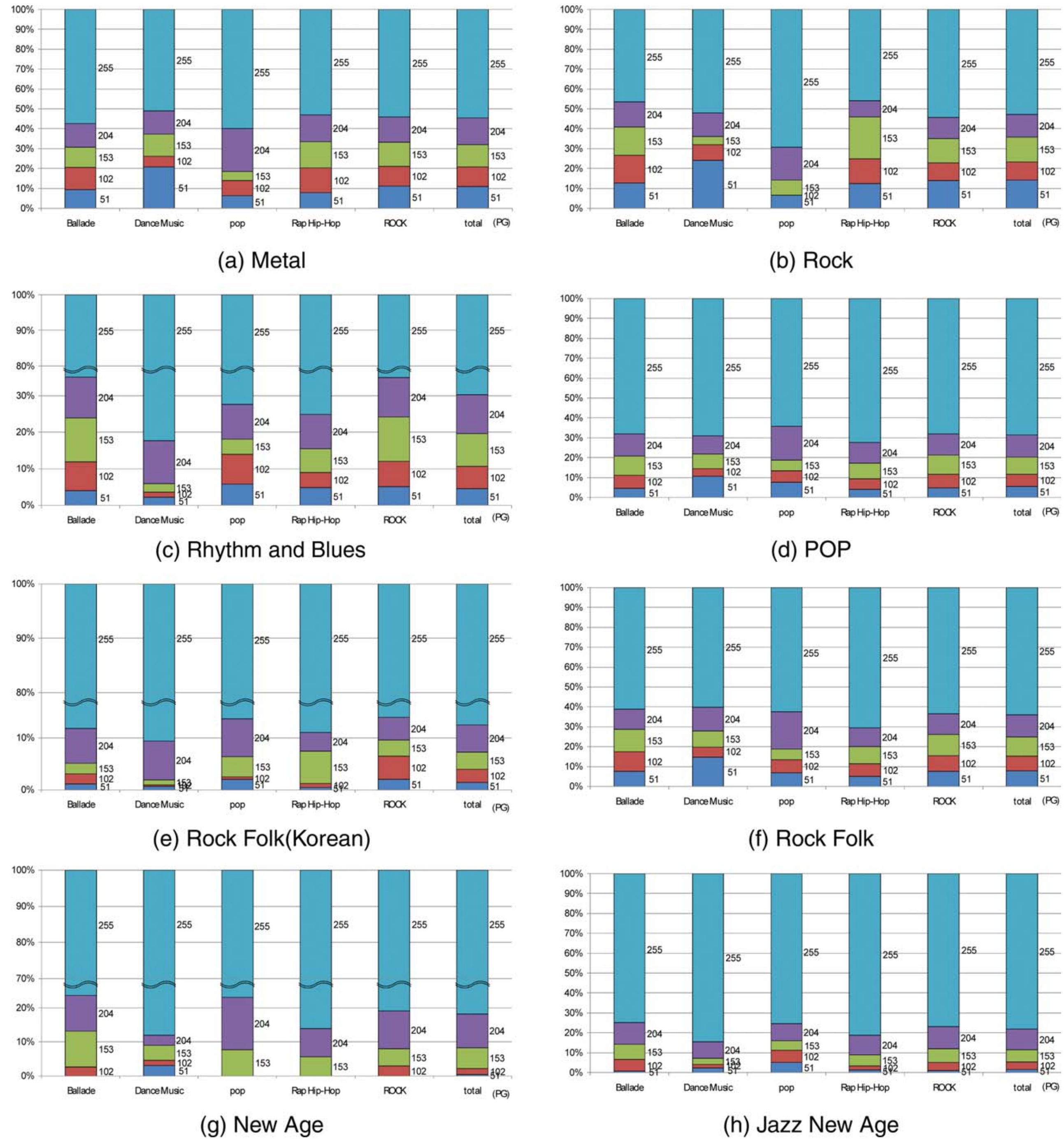


FIG. 11. Comparison of color (value) distribution of music genre for preference group (PG: preference group).

Fig. 7(b). The vertical lines marked in bold in the figure indicate the boundaries of the areas. All colors in an area are mapped to the basic color of the area.

ANALYSIS

With the data collected on mood and color, we used two-way ANOVA to verify whether the mood distributions and color distributions for the music genres depended on the listener's musical preference. After grouping 281 segments from 101 songs into eight genres, we analyzed them according to the five preference groups. Selected eight genres are obtained from classification of www.naver.com that is the most popular website in Korea. Figure 8 shows the mood distributions of the preference groups for each specific music genre, where the first five bars on the x-axis indicate the preference groups, the last bar their summation, and the y-axis shows the proportions of the 12 moods.

We used two-way ANOVA in Minitab to check whether the mood distributions evoked by the different music genres varied according to the preference group of the listeners. The results are shown in Table III. In this study, arousal and

TABLE IV. Results of two-way ANOVA of color according to the music genre.

DV	Hue value			Saturation value			Value value		
IV	PG	MG	PG*MG	PG	MG	PG*MG	PG	MG	PG*MG
df	4	7	28	4	7	28	4	7	28
F_0	3.46	46.8	2.96	17.63	720.07	11.05	72.42	711.17	31.89
P value	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

PG: preferred genre; MG: music genre; PG*MG: interaction; DV: dependent variable; IV: independent variable.

valence were defined as the dependent variables and music genre and preferred genre were defined as the independent variables (Table III). As shown in Table III, the *P* values for arousal and valence were both 0.000. Therefore, the null hypotheses could be rejected and the alternative hypotheses could be adopted: the distributions of arousal and valence are affected by the preferred genre or the music genre. The *P* values for the interaction between the preferred genre and the music genre were also 0.000, so the alternative hypotheses can be adopted: the distributions of arousal and valence are also affected by combinations of the preferred genre and the music genre.

The graphs in Figs. 9–11 show the color distributions of the preference groups for particular music genres and the *x*-axis of all graphs indicates the preferred genres. The *y*-axis of Fig. 9 indicates the proportions of the hue values for the six basic colors shown in Fig. 7; the *y*-axis of Fig. 10 shows the proportions of the saturation values (51, 102, 153, 204, and 255); and the *y*-axis of Fig. 11 shows the proportions of the value values (51, 102, 153, 204, and 255). Note that the real hue values were used for the two-way ANOVA, but the six hue values were used to display the hue distributions in Fig. 9.

We used two-way ANOVA to analyze the relationships between color and musical preference. To determine whether the color distributions of the music depended on the music genre or the preferred genre of the listener, hue, saturation, and value of the HSV model were defined as the dependent variables in this study and the music genre and preferred genre were defined as the independent variables (Table IV). The results of two-way ANOVA showed that the P value for the hue of the preferred genre was 0.008 and the other *P* values were 0.000. Therefore, the alternative hypotheses can be adopted: the distributions of hue, saturation, and value were affected by the preferred genre of the listener or the music genre presented. These results also show that hue, saturation, and value are affected by combinations of the preferred genre and the music genre.

CONCLUSION

We collected data about the moods evoked by music and the colors associated with different mood words, and analyzed them to determine whether the mood distributions and color distributions evoked by a music genre depended on the listener's musical preference. The moods evoked by music and the colors associated with different mood words were investigated in recruited volunteers, and were evaluated with two-way ANOVA. Our results showed that both mood and color are affected by different combinations of two factors, the preferred genre and the music genre presented. From these results, we conclude that the feelings of someone listening to music can be enhanced by matching the color of the ambient illumination to the mood evoked by the music played, after the listener's preferred musical genre and the genre of the music presented are considered.

The main contribution of this study is our confirmation that the listener's preferred music should be considered when selecting the color to match the music presented; however, in this study, only the preferred musical genre of the listener was considered. In future research, we will consider other personal attributes, such as age, music listening time, and sex, to allow us to offer a much better service to the listener. Currently, musical genres taken from popular music are only considered and so it is also interesting to check that the same results can be obtained for other musical genres like classical music. Also, here, only basic associations between mood and color for different musical preferences are analyzed. Thus, it will be more significant for someone to look for specific associations: for examples, would someone who is an R&B mania choose more saturated colors to describe R&B music than a non-R&B fan? Would someone who is a Rock mania choose colors with lower luminosity for Rock music than a non-Rock fan? and so forth. To reduce complexity, in this study, six basic colors instead of 216 colors are used in analyzing the basic associations and so it's not guaranteed that the same results can be obtained when 216 colors are used. We also leave this question as a future work because too much data is required to examine the question.

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BOOK REVIEWS

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constancy in our vision can be better modeled as a mechanism that synthesizes the appearance from the spatial distribution of the stimuli. This mechanism has the useful advantage of discounting a big part (rarely the whole) of possible dominant color present in the scene. Computer vision for a long while kept working assuming the original formulation of the mechanism, aiming at completely discounting the illuminant or reversely estimating and/or removing the illuminant (completely). But this is not a flaw of the book that, as stated clearly in the title, aims at focusing on computer vision. The only pity is to present this interesting problem too quickly in the introduction, especially the relationship between human and computer vision color constancy.

Regarding computer vision color constancy, the book presents a structured survey, starting from the formulation of the ill-posed problem of illuminant estimation and the subsequent application of a possible chromatic adaptation. Then, the section introduces models of color constancy using low-level features, presenting the Gray-World assumption and many methods for illuminant estimation, such as for example, Gray-Edge, ending with a quick outline of physics-based methods. The following methods for color constancy are the gamut-based ones with a quick, but wide description of the gamut mapping problem. Color constancy using machine learning are the last methods presented. To end the section, methods and databases to evaluate computer vision color constancy are presented, together with some experiments.

Part four regards the extraction of color features. Starting from color feature detection the book enters a very hot topic in computer vision and extends many techniques classically applied to black and white images to the use of color, introducing the formulation of color tensors and color saliency. After the detection of the color features, it follows their description. Here, the book presents Gaussian derivative-based descriptors with their characteristics of use. The last chapter of this section describes different methods of color image segmentation. The techniques presented are based on Gabor filtering, color textures, material recognition using invariant anisotropic filtering, color invariant codebooks, material-specific adaptation, and Delaunay triangulation. Also in this section, are a series of hands-on experiments for the reader.

Practical applications of the many presented techniques play a relevant role for the authors and for this reason the last part is completely dedicated to a series of applications, important for many computer vision scientists. Included are: object and scene recognition, color SIFT (Scale-Invariant Feature Transform) descriptors, color naming, segmentation of multispectral images, distance measures of photometric invariants, and more.

Finally, a large updated reference list helps the reader to investigate further about every topic presented in the book.

The authors are well-known scholars in the field of color and computer vision, and they acknowledge the rich contributions of many more scholars from both the fields.

This book can be of interest for researchers and professionals in computer science, computer vision, image processing, electrical engineering, and signal processing who want to extend their research to include color information. It also can be helpful for scholars from the above fields who want to compare their techniques with alternative techniques of this dynamic and expanding field.

A. Rizzi

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