Automatic Music Selection Algorithm Based on Background Image

Sooyoung Cho, Deayeol Kim, Sinwoo Yoo, Kyounghak Lee, Chae-Bong Sohn

Abstract Background/Objectives: Game music has the characteristic in which determined music is repeated according to the area in the game.

Methods/Statistical analysis: In this paper, we propose an algorithm in which various music is repeated in game. The game background is extracted to the image by utilizing the screen-shot function. First, gave the histogram of similar images. The classification of the background is determined using the learned histogram, and one of the music corresponding to the tag created by the user is reproduced.

Findings: For each image, a histogram was determined. RGB and lab histograms are represented through the table. As a result, you can see that game screenshots and other images were judged to be similar images when they were entered.

Improvements/Applications: It can be used for video processing and other editing functions. Learning through algorithms can be used in many ways.

Keywords: Back ground Music, Game, Histogram, Back ground image, CIE Lab

I. INTRODUCTION

A video game consists of a visual and audio element basically. Considering background music or sound effects as the one of them they have a tendency to be set or configured to play limited assets in one world or scenario in common. This paper suggests a method to select a proper musical asset as a background music depending on the given background image from prepared musical assets. The given background image extract meaningful information of which the overall brightness and color from the image of itself. Images of having a similar color distribution show also a similar characteristic of the color histogram distribution of their own. The way of suggesting utilizing this characteristic is a choosing background music asset based on the result of the learning process with the information of all given background images. A trained result from given all color histogram information will suggest the most likelihood of background music asset to be played for the background image of the current moment.

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Sooyoung Cho, Deayeol Kim, SinwooYoo, Department of Electronics and Communications Engineering, Kwangwoon University 20 Gwangun-Ro Nowon-Gu Seoul, 01897, Republic of Korea.

Kyounghak Lee, IACF, Kwangwoon University, Korea.

Chae-Bong Sohn, Department of Electronics and Communications Engineering, Kwangwoon University 20 Gwangun-Ro Nowon-Gu Seoul, 01897, Republic of Korea.

E-mail:cbshon@kw.ac.kr

II. MATERIALS AND METHODS

2.1. Game Music characteristics

Most of game music in most of the actual video games play several limited assets for a designated world in the game. The background music which is being played in Henesys region keeps repeating, in the game named Maplestory in an example.

Table 1: Maple Story BGM in Henesys

Map Name	Music
Hnessys	Floral Life
Hnessys market	Go Picnic
Hnessys field 1	Cava Bien
Hnessys field 2	Rest N Peace
Hnessys field 3	Blue Sky

And we can find a similar case in other games such as World of Warcraft as well.

Table 2: World of WarCraft BGM in Black Temple

Sequence	Music
1	The Black Temple
2	Karabor Sewers
3	Gates
4	Sanctuary of Shadows
5	The Reliquary of Souls
6	The Storm Summit
7	Illidan and Akama
8	Stormrage

2.2. Classification of Music

Each of the musical assets is classified and tagged by which has a similar tone before the suggested logic performs.

2.3. Measure image similarity

The similarity at large associates to perform this image classification process. This is shown in [Figure 1].

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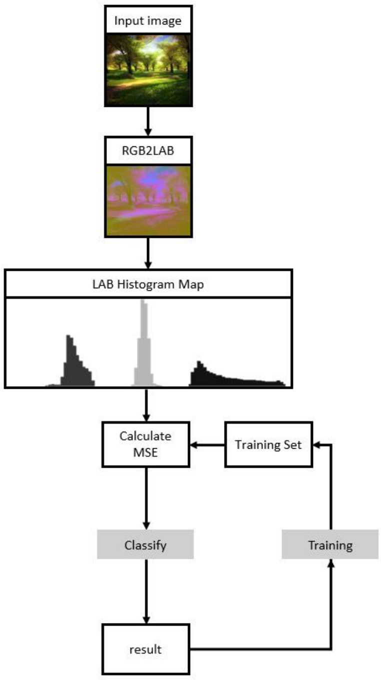

Figure 1. Classify image using lab Histogram

2.3.1. Characteristics of CIE Lab

CIE Lab is one superior method to convert an RGB to a color value in visual. What each of the three values means as below[1-3].

Table 3: Meaning of each Lab channel

Channel	Meaning
CIE L*	Lightness component
CIE a*	Red-green component
CIE b*	Yellow-blue component

Step 1: RGB value needs to preprocess to 3-dimensional coordinate in order to finish the conversion process and explanation of the used formula and its calculation is below[4].

$$X = 0.490 * \text{Red} + 0.310 * \text{Green} + 0.200 * \text{Blue}$$

$$Y = 0.177 * \text{Red} + 0.813 * \text{Green} + 0.011 * \text{Blue}$$

$$Z = 0.000 * \text{Red} + 0.010 * \text{Green} + 0.990 * \text{Blue}$$

$$L^* = 116f\left(\frac{Y}{Y_n}\right) - 16$$

$$a^* = 500\left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right]$$

$$b^* = 200\left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right]$$

$$f(t) = \begin{cases} t^3 if t > 6/29^3 \\ 3(6/29)^2(t - 4/29) otherwise \end{cases} \quad (1)$$

2.3.2. Histogram Sensitivity

A histogram represents the all classified data in certain ranges from the image and shows them as aligned bar graphs. Each of the range is called as a bin. The chosen scale of these bins affects the result of the suggested solution, e.g., a too narrow range of the bin makes the selection of asset unnecessarily dramatic, and a too wide one does it too insensitive.

2.3.3. Histogram Equalization

The normalization process regulates the overall histogram levels as its purpose, a biased brightness distribution is needed to be uniform and this process improves the overall balance of contrast [5-6].

2.3.4. Training set

The dataset for the training process is prepared before measuring the image similarity among the asset. Each of 20 background images is grouped depends on how many kinds of background images are needed to be classified, and Each of histogram element has a gain value in order to have a median.

2.3.5. Measure Similarity

Step 2: The similarity among images in the training set is calculated by this formula as below.

$$X = \sum_{i=0}^{\frac{N}{cell}} \Delta L_i^2$$

$$Y = \sum_{i=0}^{\frac{N}{cell}} \Delta a_i^2$$

$$Z = \sum_{i=0}^{\frac{N}{cell}} \Delta b_i^2$$

$$\text{similarity} = \sqrt[2]{X + Y + Z} \quad (2)$$

This result of the calculation process classifies given background images in the dataset by the color distributions and distances.

2.4. Music selection using similarity

We propose the following method as shown in [Figure 2]. That considers the calculated similarity defines how much of images shares their chromatic aberration. The selection of the most proper background music for the given background image depends on this similarity level[7-10].

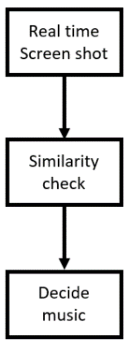

Figure 2. Proposed method

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III. SIMULATION

3.1. Testing to Training set

The dataset that performs the training process consists of pictures of actual landscapes shown in [Figure 3]. The test image is shown in [Figure 4].

Figure 3. Tag1 ~ 3 training image

Figure 4. Test scene 1 and 2

Table 4: Simulation result using RGB histogram

	test 1	test 2
Tag 1	610.38	666.87
Tag 2	823.33	710.19
Tag 3	622.80	542.91
result	Tag 1	Tag 3

Figure 5. RGB-histogram for Fig 8

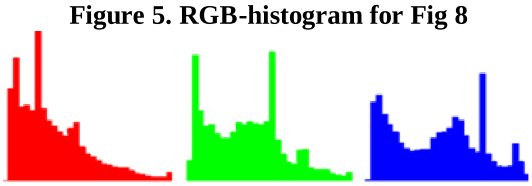

Figure 6. RGB-histogram for Fig 11

Table 5: Simulation result using Lab-histogram

	test 1	test 2
Tag 1	351.52	207.16
Tag 2	444.57	274.74
Tag 3	379.30	208.16
result	Tag 1	Tag 1

Figure 7. Lab-histogram for Fig 8

Figure 8. Lab-histogram for Fig 9

IV. RESULTS AND DISCUSSION

[Figure 5-8] and [Table 4-5] is shown the histogram of the proposed method. This suggested method confirmed that this chromatic aberration similarity performs well to figure which kind of background music would be chosen for the given background image, except a condition of changes exceeding a certain limit of the background image from the one before. Every dataset element has tagged via only personal preferences and decisions, so the result of this selection should be considered in a general way. This overall result can be regarded it could be better in case of applying machine learning technique in the classification process of the image and music assets. This also may big help for better media production programs.

V. CONCLUSION

In this paper proposes a music selection algorithm based on the background image. In a real game environment, one music is played repeatedly on one wallpaper. However, by using the proposed algorithm, you can see that several songs are executed repeatedly. We believe that by applying image processing techniques to the computer game environment, users will be more effective in creating a more boring environment. In the future, we will be able to get better results if we apply the advanced deep learning model to the image classifier and develop it by applying the model that generates the music. It's also seems to be able to present a new paradigm in the selection of game background music.

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