한국환경생태학회지 22(3) : 289~300. 2008
Kor. J. Env. Eco. 22(3) : 289~300. 2008

Discriminant Analysis of Natural Landscape Features in National Parks between Korea and Scotland[1]

- Using Low-Level Functions of Content-Based Image Retrieval -

Dukjae Lee[2]

한국과 영국 사이의 국립공원 자연 경관 특색의 판별 분석[1]

- 내용기반 영상검색의 저단계 기능 측면에서 -

이덕재[2]

ABSTRACT

This study aims to discriminate differences in natural landscapes between the Cairngorms National Park in Scotland and the Jirisan National Park in Korea, using functions of content-based image retrieval such as texture, shape, and color. Digital photographs of each National Park were taken and selected. The low-level functions of photographic images were reduced to orthogonally rotated five factors. Based on the reduced factors, a linear decision boundary was obtained between Cairngorms landscapes and Jirisan landscapes. As a result, the discriminant function significantly delineated two groups, resulting in x^2=63.40 with df=5(p<0.001). Both the eigenvalue 2.417 and the value of wilks' lambda 0.29 supported that the most proportion of total variability came from the differences between the means of discriminant function of groups. It was estimated that four independent variables explained about 70.7% of total variance of dependent variable. The variable with the largest effect on landscapes was far region-related factor(r=1.07), followed by near region-related factor (r=0.90). A total of 90.7% of cross-validated grouped cases were correctly classified. It was interpreted that far distant regions, as well as near distant regions, had sufficient discrimination power for landscape classification between the Cairngorms National Park and the Jirisan National Park, so that landscape identity of the National Park over cultures was revealed by skylines in a most effective way. Relatively fewer factors making visual landscapes were effectively used to classify natural landscapes of the National Parks which had different semantics.

KEY WORDS : SCOTTISH LANDSCAPE, PHOTOGRAPHIC IMAGE, LANDSCAPE IDENTITY

요 약

질감, 모양, 색채 등 내용기반 영상검색(CBIR)의 기능을 이용하여 한국의 지리산 국립공원과 영국의 케이른고럼스 국립공원의 자연 경관에 있어서의 차이를 판별하는데 본 연구의 목적이 있다. 먼저 각 국립공원의 자연경관을 디지털 사진영상으로 촬영한 후, 전형적인 경관사진을 선별하였다. 사진영상의 저단계 기능(Low-level function)이 계량화되어 수직적으로 회전된 다섯 개의 요인으로 축약되었다. 이 중 유의한 차이를 보이지 않은 물 관련 요인이 제외된 나머지

1 접수 8월 15일 Received on Aug. 15, 2007
2 상지대학교 산림과학과 Dept. of Forest Science, Sangji University, Gangwon(220-702), Korea(dukjlee@sangji.ac.kr)

네 개의 요인에 근거한 판별선이 케이른고럼스 경관과 지리산 경관 사이에서 도출되어, 판별함수가 두 그룹을 유의하게 분할하였다(x^2(4)=61.433; p<0.001). 고유치 2.417과 윌크스 람다 0.293에 의하여 전체 변이가 두 그룹의 판별함수 평균의 차이에서 대부분 산출되었음을 확인하였다. 또한, 네 개의 독립변수가 종속변수 전체 분산의 70.7%를 설명하는 것으로 추정되었다. 경관에 대하여 가장 큰 효과를 나타내는 변수는 원거리관련 변수(r=1.073)이며, 다음으로 근거리관련 변수(r=0.896)였으며, 전체적으로 90.7%가 타당하게 분류되었다. 이는 케이른고럼스 국립공원과 지리산 국립공원 자연경관 사이에서 사진영상의 근거리 요인뿐만 아니라, 원거리 요인이 보다 경관 차이에 유의한 판별력을 보이는 것으로 해석되므로, 국립공원의 경관정체성과 관련한 원거리 스카이라인의 시각적 중요성을 보여주는 것이라 하겠다.

주요어 : 스코틀랜드 경관, 사진영상, 경관정체성

INTRODUCTION

Visual landscape of the National Park in Korea has been a salient subject for the park management(Bae, 1997; Koh, 1997; Im and Shin, 1998; Han, 2005; Lee, 2006; Kim and Huh, 2007). Landscape is determined by various factors including geology, geography, soil, climate, history, and culture. While landscape involves the characteristics of culture formed by various factors, it is fundamentally perceived and differentiated by human senses. For instance, although man's perception of beauty might be controversial, man's effort to make a landscape change into a different shape is certainly related to the arrangement of things on the visual perception. Visual elements are important factors in reorganizing landscape (Russell *et al.*, 1980). Texture, shape, and color, which are useful to depict landscape image, have been used as the fundamental elements in the field of content-based image retrieval (CBIR). CBIR is the system to develop methods to archive, query and retrieve visual data based on their content, assuming images would be indexed by their own visual content(Rui and Huang, 1999; Antani *et al.*, 2002).

The elements are often called low-level functions that are based on the visual contents of photographic images and that are subsequently related to human vision. Low-level functions are efficiently used to retrieve, classify, and search the image database(Vailaya *et al.*, 1998; Rui and Huang, 1999; Antani *et al.*, 2002; Cheng and Chen, 2003; Wang and Zhang, 2004). Although semantic description of image is also used for image retrieval and classification as a high-level function, also called the lexical basis function(Black *et al.*, 2003), this high-level function depends more upon each individual, needs more complex interpretation, and does not directly decompose the image into visual elements. The low-level function that is related to human vision is more acceptable to visual image analysis. The level of image content is determined by the source of visual information which constitutes the content of images.

Similar to the general information level of image content, landscape elements of photographic images can be divided into three levels. 1) Low-level is related to human vision. 2) Middle-level is related to a structure between the low-level functions. Complex landscape design elements are included in this middle-level. Finally, 3) high-level is related to psychological semantics. Cultural meaning is of importance in the high-level, and landscape has a mental image characteristic at this high-level stage. Until now, visual landscape elements on the middle-level have been used and categorized by landscape design or architecture, because the interrelated structure between elements is thought of as the representation of complex real world landscape. Landscape design is primarily concerned with visual relationships, in addition to the technicalities of materials, dimensions, and details. Fairbrother(1970) suggested that the elements of landscape included landform, water, vegetation, and the structure of ground, wood, and water. As the part of the visual design, grass was specially considered as the ground cover in utility areas and the open space. Lucas(1991) proposed aesthetic-related visual elements. According to him, design principles for aesthetic appreciation of landscape were summarized as shape, scale, visual forces, diversity, and unity. Shape was composed of the edges of planes and volumes and with lines. Scale was concerned with relative size. Visual forces occurred when a static image gave an illusion of movement, which depended upon the scale and irregularity of the landform. Diversity was interpreted as a result of varied geology, climate, and human use. Unity was achieved when the various parts were organised into a clearly identifiable composition.

According to Ervin(2001), landscapes could be understood as usually composed of six essential elements in combination: landform, vegetation, water, structures (including architecture and infrastructure), animals(including people), and atmosphere(including sun, wind, etc). Appleton and Lovett(2003) tried to classify two sets for landscape elements; i.e. main elements and auxiliary elements. Main elements were the parts of elements usually under direct consideration in environmental decision-making, such as color, procedural texture, image texture, and plants. Auxiliary elements were considered to help viewers in relating a visualization to real life, such as sky, water, and shadows. Arriaza *et al.*(2004) suggested several measurement scales in order to measure the intensity of the landscape elements, such as water, land cover and type of vegetation, topography, man-made elements, number and contrast of colors, presence of alignments, scale effect, focal view, texture, and wilderness.

Numerous landscape elements increase the complexity of determining landscape value(Litton, 1982; Lamb and Purcell, 1990; Purcell, 1992; Purcell *et al.*, 1994). The main difficulty with the middle-level function lies in its complexity. Practically, there is much more need in terms of processing time and power due to the complicated geometry of the numerous elements, while the low-level function is relatively simple and straightforward to determine a visual aesthetic. Some landscape architects pointed out fundamental landscape elements on the low-level basis. Cornford and Dale(1990) proposed scale, style, and color as landscape design elements. Colvin (1990) suggested three basic elements such as form, color, and texture. The Institute of Environmental Assessment and the Landscape Institute(1995) defined landscape as the appearance of the land in a common sense, and described that shape, texture, and colors were included in this landscape. The Institute also argued that specific patterns that were distinctive to others were created by the combination of the various components of these elements.

While the landscape at the middle-level is usually judged by landscape experts, judgement based on low-level function is not necessarily implemented only by experts. The low-level function also provides straight interpretation and quantitative measure, which ultimately provides a basis for drawing a predictive model for landscape preference. It can be used to classify the landscapes by the quantified visual elements, which makes it possible to draw a decision boundary. Due to this advantage of the low-level function, scientific approaches to the evaluations of the visual landscapes have been attempted by the application of Digital Image Processing (DIP) in which landscape is segmented into sub-regions (Steinitz, 1990; Brown, 1994; Hehl-Lange, 2001; Appleton and Lovett, 2003; Arriaza *et al.*, 2004).

As mentioned, while the classification of landscape can mostly depend on the semantic meaning of it, recognition of each landscape is certainly based on the visual capacity of humans. It is assumed that landscape involving cultural meaning would be also classified by visual elements. Based on low-level function, image classification has been undertaken according to its semantic scale in order to simplify the procedure of landscape assessment(Vailaya *et al.*, 1998; Jain *et al.*, 2000). Vailaya *et al.*(1998) have attempted to cluster photographic images into semantically meaningful categories(i.e. rural or urban landscape) using low-level functions of images that are often described by visual elements such as texture, shape, and color. Because the purpose of their research is on grouping an image by its function, they do not reveal the degree of difference in measurement between images. However, this has an advantage of simplifying complex characteristics of landscape using low-level function instead of middle-level. In this study, thus, low-level functions of digital landscape images were proposed in order to discriminate difference in natural landscape that was classified as either the Cairngorms National Park or the Jirisan National Park in which semantic-based identity was fundamentally involved when being designated. Methodologically, a linear decision boundary using discriminant analysis was formulated to determine difference in visual landscape between the Cairngorms National Park in Scotland and the Jirisan National Park in Korea.

LOW-LEVEL FUNCTIONS OF PHOTOGRAPHIC IMAGES

Photographic images are composed of low-level functions such as texture, shape, and color in terms of classification of visual things. Among them, texture plays an important role in visual composition of natural landscapes. Texture element is defined by a uniform intensity region of simple shape in the image. A region is a collection of adjacent pixels in the digital image. Texture is a visual property of images suitable to the characterization of image content. It is an innate property of virtually all surfaces and features such as vegetation, water, and sky. A totally uniform image region has texture. In other words, any image region that can be perceived as being spatially homogeneous in some sense can be characterized by its texture. For instance, vegetation area is recognised as homogeneous region that provides different texture from non-vegetation area.

Texture provides important cues to recognize real objects. Features based on texture are often useful in automatically distinguishing between objects and in finding boundaries between regions. In addition, texture in an image can be perceived at different scales(Lucas, 1991). Texture varies when seen at different distances. The scale of observation is fundamental to texture perception. There may be several levels of completely different textures in the same image but at different scales. Scale in a photographic image is usually divided into three regions according to its distance from an observant point of view, e.g. far-distant-view, middle-distant-view, and near-distant-view(Shafer *et al.*, 1969).

People usually concentrate most of their attention on the borders between homogeneous regions, so that image is often segmented into a number of regions, each of which is reasonably uniform in same characteristic segments by texture. Accordingly, a recurring theme in scene analysis is that a picture may be simplified by representing regions in the picture by their outlines(Jain and Zongker, 1997). The procedure to extract regions covered with the same texture to detect edges between different textures is called image segmentation. In computerized image analysis image segmentation is the first step to divide the image into regions that correspond to various objects in the scene. Then, various characteristics such as size, shape, and color can be measured for each region. The advantage of this approach to segmentation by texture lies in the quantitative basis on image analysis, whereas other researches provide only qualitative basis, e.g. presence/absence of skyline(Vailaya *et al.*, 1998; Arriaza *et al.*, 2004).

Shape is shown as a region or boundary of a represented image. Although shape ranges from simple and geometric to complex, it is inherently complex to represent. For instance, natural scenery displays a wide range of shape and form which is usually irregular but some are geometric at a small scale. Shape representation of a digital image can be achieved by boundary-based edge detection or the homogeneity-based region growing technique. The shape of a region is described in terms of the scalar measurements that are based upon area width and perimeter length. Although a ratio of any two lengths in an image could be used as a size-invariant shape measure, the unit-free measure does not provide direct interpretation with a view of comparison. Both area and perimeter, thus, can fundamentally be used for the basis of shape as well as for the comparison of measure.

Color is a visual feature that is immediately perceived when looking at an image. Because humans distinguish more color than just a grey shade, color images are often represented by the intensity of images. color is an important factor in aesthetic preferences(Kaufman and Lohr, 2004). Garcia *et al.*(2003) argued that both color and location were the most important elements, although all visual elements were influential in the integration of environment. Hands and Brown(2002) also suggested that there were two main variables for visual preference, i.e. color and human intent. There are several methods of organizing and describing color; e.g. Red-Green-Blue (RGB) model, Hue-Saturation-Value(HSV) model, Cyan-Magenta-Yellow(CMY) model, International Commission on color model, etc. A color model is a particular representation of color and the model permits the precise specification of color. Each model has a different way of representing, characterizing, and categorizing color. Among them, the RGB color model can be used to represent the distribution of image intensities for measurement. In the model, images are represented in terms of red, green, and blue components. A particular mix of the red, green, and blue components of a screen area corresponds directly to the perceived color of that area. Other colors are made by mixing these together. RGB color can be seen as a three dimensional space(Figure 1) and the values are often in the range [0,1] or [0,255]. The advantages of RGB include that it is linked to the way human eyes work and

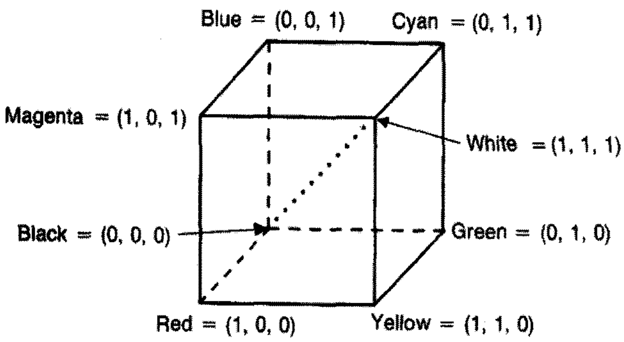

Figure 1. RGB color space(Foley *et al.*, 1995)

that it is based on the linear numeric scale.

MATERIALS AND METHODS

The Cairngorms National Park in Scotland and the Jirisan National Park in Korea were selected as typical natural landscapes for each cultural group in order to discriminate landscape differences. A National Park is closely related to a typical landscape in that the Park shows representativeness and ideal of natural landscape (Lee, 2006). Because of consistent landscape conservation effort in the National Park, a typicality of the Park reveals landscape difference from other landscapes of different regions. The Cairngorms National Park shows the typical landscape of central Highland region of Scotland. Cairngorms is classified as the representative one of the National Scenic Areas(NSAs), and geographically located in the central Highlands of Scotland. The Cairngorms National Park, is a new and the second National Park in Scotland. The most impressive topography of the Cairngorms is characterized by the extensive summit plateaux at about 1,000m, with accompanying rock-cliffs and ex-glacial features of lochs(lakes) and glens(valleys).

In a similar vein, the Jirisan National Park shows the typical landscape of southern mountain region of Korea. Jirisan is included in the Baekdudaegan representing Korean mountains and a range of mountains. Also, a landscape component of it makes Jirisan one of the representative Parks in Korea. The contrast and the harmony created by the mountain landscapes with dense forest evoke the sense of abundance of Korean landscapes. The Jirisan National Park, located in the southern central part of Korea was established as the first National Park in 1967. The physical features of the area are distinctive with a rolling plain, hills and mountains culminating in the highest peak of Cheonwangbong(1,915m) in the eastern part of the mountain.

The photographs of natural landscapes were taken and selected for both the Cairngorms National Park and the Jirisan National Park. Using a 2.11 million pixel digital camera, landscape photographs were taken at major view points through the main footpath of the Cairngorms National Park(i.e. Lairig Ghru, 43㎞) from June to September 2002, and through the Jirisan National Park(i.e. Nogodan-Cheonwangbong, 25.5㎞) from July to August 2003. A total of 54 digital photographs showing the typical natural landscapes of the National Parks were selected by the visitors who were familiar with their landscapes; i.e. 27 photographs selected by 26 visitors in the Cairngorms and 27 photographs selected by 30 visitors in the Jirisan, respectively.

In order to generate variables of low-level functions of landscape photographs(i.e. texture, shape, and color), digital image processing(DIP) was used with photographs of each National Park. A photographic image was segregated into the 8 different regions in which landscape features were represented by different textures such as vegetation by distance, water, and sky, suggested by Shafer *et al.*(1969). Each segregated region was then quantitatively evaluated by both 2 scalar measure(i.e. area and perimeter) and 3 RGB color value, resulting in 40 variables of low-level functions of landscape photographs. Figure 2 shows that the Area of Interest(AOI) based on

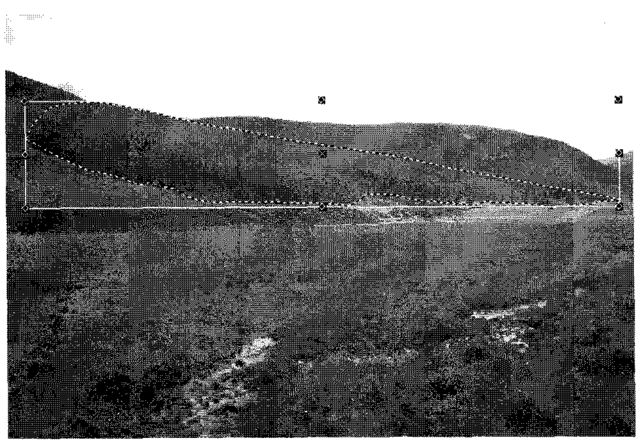

Figure 2. Demarcating the AOI using screen digitizing technique

Table 1. Example of area, perimeter, and RGB Color value

Texture		Shape		color		
Distance	Feature	Area*	Perimeter*	Red	Green	Blue
Middle	Vegetation	115340	2514	0.343	0.353	0.398

* Number of pixels

different texture was demarcated using a screen digitizing technique of ERDAS 8.3 IMAGINE software(Schrader, 1997). Area, perimeter, and RGB color value were obtained within the AOI(Table 1).

A distinctive landscape photograph relative to other landscape photographs was said to have a large discrimination power if its "within-class" distances were small and the "between-class" distances were large. Discriminant analysis(DA) was a statistical technique in data classification through finding a linear decision boundary that maximized the variances "between-class" relative to "within-class"(Theodoridis and Koutroumbas, 1999; Everitt and Dunn, 2001). Data matrix X was divided into two sub-groups described as a group matrix H. The matrix of the centroid of each group($\overline{X}_g$) and the total centroid($\overline{x}'$) were calculated as follows(Everitt and Dunn, 2001).

$$\overline{X}_g = (H'H)-1 \times H'X$$

$$\overline{x}' = (1/N) \times 1'X$$

Matrix of "within-class" deviations (P), matrix of "between-class" deviations (Q), and matrix of total sample deviations (U) were calculated.

$$P = X - H \cdot \overline{X}_g$$

$$Q = H \cdot \overline{X}_g - 1 \cdot \overline{x}'$$

$$U = X - 1 \cdot \overline{x}' = P + Q$$

Then, "within-class" Sums of squares and cross products(SSCP) matrix (W), "between-class" SSCP matrix (B), and total sample SSCP matrix (T) were obtained.

$$W = P'P$$

$$B = Q'Q$$

$$T = U'U = W + B$$

The desired vector of discriminant weights (K) was calculated as follows.

$$K = C_w^{-1} \times d$$

where, C_w^{-1} is the inverse of covariance matrix from the within groups SSCP matrix W, and d is the difference vector between group centroid from $\overline{X}_g$.

Fisher(1936, 1938)'s linear discriminant function (t) was obtained, which produced the predicted discriminant classification score (D).

$$t = X_d \times K$$

where, X_d is the n × p matrix of mean-corrected scores on the original predictors.

The meaning of the discriminate functions is deduced by the correlation between functions and predictors, called loadings A.

$$A = R_w \times t_s$$

where, Rw is the matrix of within group correlations, and ts is the standardized discriminate function coefficient.

RESULTS

To decide how may factors were needed to represent whole sets of data among 40 variables of low-level functions of landscape photographs, eigenvalue greater than 1 from the result of Principal component analysis (PCA) suggested 5 components(Figure 3). Near region-related landscape component was summarized as the first factor (F1); middle region-related as the second(F2), water-related as the third(F3), far region-related as the fourth (F4), and sky-color-related as the fifth(F5). Near region was defined as near distant landscape in the photographs where individual features are discernable; middle region as middle distant landscape in the photographs where individual features are recognizable but not in fine detail; far region as far distant landscape in the photographs where individual features are not distinguishable yet, as Shafer *et al.*,(1969) suggested.

Five common factors explained 88.75% of the total visual elements of landscapes and sufficiently represented

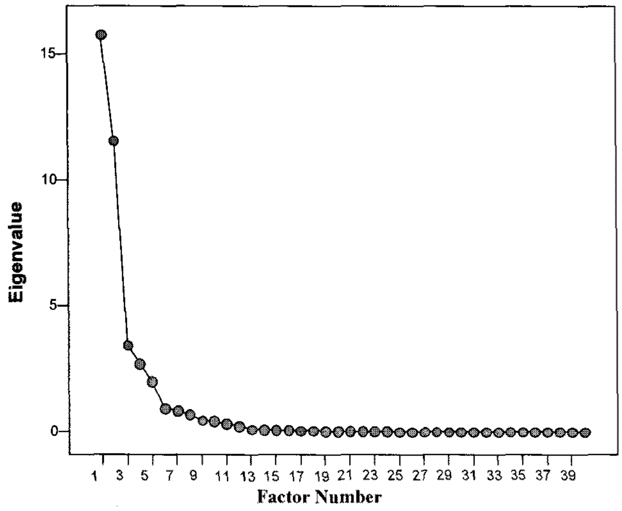

Figure 3. Reduction of variables based on eigenvalue

the characteristics of the photographs that composed the low-level functions. Factor scores of 5 components were subsequently obtained. Characteristics of summarized data of each National Park photograph is shown in Table 2.

Discriminant analysis(DA) using a stepwise method was executed between two photo-groups, i.e. 27 Cairngorms photographs and 27 Jirisan photographs. There were some statistical assumptions that needed to be checked. Sample size sufficiently exceeded the number of predictors and equal between groups, so that the homogeneity of variance-covariance matrices was not a concern. Multicollinearity was also not a problem for five factor scores, because these reduced factor scores had no significant correlation with each other after the rotated PCA. A mahalanobis distance was calculated to find the multivariate outliers within a photo-group that subsequently needed some variable elimination or transformation for discriminant analysis(Table 3). With the critical value of the mahalanobis distance $x^2(5)$ = 20.515(p<0.001), there was no multivariate outlier for each group.

It was also necessary to examine the difference between two groups over independent variables. Equality of group

Table 2. Characteristics of summarized factor scores

Group		F1	F2	F3	F4	F5
CNP[a]	Mean	0.455	0.254	-0.121	0.621	0.193
	S.D.	0.776	1.310	0.728	1.031	0.479
JNP[b]	Mean	-0.455	-0.254	0.121	-0.621	-0.193
	S.D.	1.003	0.434	1.215	0.419	1.316

[a]: Cairngorms National Park photographs [b]: Jirisan National Park photographs
F1: Near region-related component, F2: Middel region-related component, F3: Water-related component,
F4: Far region-related component, F5: Sky-color-related component

Table 3. Finding multivariated outliers based on a mahalanobis distance

CNP	dist.	CNP	dist.	JNP	dist.	JNP	dist.
C611001	1.97	C816013	10.23	J724002	1.74	J801021	1.62
C611026	2.68	C816019	5.48	J724003	5.44	J801026	2.18
C611031	2.60	C816021	11.09	J724005	5.54	J801027	6.50
C611035	2.94	C816038	2.86	J724006	17.04	J801029	0.74
C611038	2.54	C816043	3.76	J724007	5.66	J801035	3.36
C611053	3.92	C816056	15.27	J724009	10.85	J802008	2.08
C603001	2.02	C816095	11.95	J724012	5.52	J802009	5.56
C603003	3.82	C816099	10.04	J724013	10.50	J802010	2.76
C603009	4.02	C816107	4.66	J801006	4.02	J802011	2.48
C603030	1.21	C915022	1.98	J801008	2.48	J802012	4.04
C603034	3.74	C915047	3.96	J801009	2.28	J802013	10.18
C603038	1.88	C915051	1.83	J801010	1.23	J802054	4.23
C603044	6.52	C915061	5.17	J801014	4.46	J802056	3.87
C501009	1.87			J801019	3.64		

Table 4. Degree of importance of each variable

Variable	Wilks' lambda	F	Significance
F1	0.789	13.878	0.000
F2	0.934	3.661	0.061
F3	0.985	0.784	0.380
F4	0.607	33.636	0.000
F5	0.962	2.060	0.157

means was tested to find any variable revealing significant differences between Cairngorms NP landscapes and Jirisan NP landscapes. The variables showing differences between the Cairngorms NP and the Jirisan NP could be F4 and F1(Table 4). Wilks' lambda is reflective of the variables' importance. The lower the value of Wilks' lambda is, the higher the percent of explained variance of the dependent variable is. F4 indicated that differences between the Cairngorms NP and the Jirisan NP accounted for 39.3% of variance.

The loading matrix of correlations is shown in Table 5, which also suggests that the best predictor in distinguishing between Jirisan NP photographs and Cairngorms NP photographs was F4. A following significant factor was F1 in distinguishing the groups of landscapes.

Hence, DA was conducted to predict group membership. Specifically, stepwise method was used to estimate discriminant function coefficients with the elimination of insignificant variables(Table 6). The discriminant function significantly discriminated two groups after eliminating the variable F3, resulting in $x^2(4) = 61.433(p<0.001)$. The eigenvalue was very high(λ=2.417), which implied that the between group differences were much greater than the within group differences. Also, the value of Wilks' lambda 0.293 supported that the most proportion of total variability came from the differences between the means of discriminant function of groups. It was estimated that four independent variables explained about 70.7% of total variance of dependent variable. The variable with the largest effect on landscapes was F4(r=1.073), followed by F1(r=0.896).

Table 5. Significant factors in distinguishing between the CNP and the JNP

Variable	Loading
F4	0.517
F1	0.332
F3	0.191
F2	0.171
F5	0.128

Unstandardized discriminant function coefficients(or, linear decision boundary) provided the classification score (D) for each landscape that classified the Cairngorms NP and the Jirisan NP. Central value of Cairngorms NP was 1.525 and that of Jirisan NP was -1.525.

$$D = 0.999(F1) + 0.558(F2) + 1.364(F4) + 0.425(F5)$$

Table 7 shows the estimated classification score for each of the landscape photographs. According to the score, the "C611001" photograph(D=1.682) showing minimum distance from the estimated central value was regarded as the most representative landscape of the Cairngorms NP, whereas the "C816021" photographs(D=-1.767) was the least one(Figure 4). Likewise, the "J802010" photograph (D=-1.566) showing minimum distance from the estimated central value was regarded as the most representative landscape of the Jirisan NP, whereas the "J802013" photographs(D=-0.707) was the least one(Figure 5).

A predicted model(PM) for the classification of Cairngorms NP landscape over Jirisan NP landscape based on four visual factors were formulated by the Fisher's linear discriminant function.

$$PM = -1.857 + 1.524(F1) + 0.852(F2) + 2.081(F4) + 0.648(F5)$$

DA also revealed that for both Cairngorms NP landscapes and Jirisan NP landscapes a high percentage of the cases(85.2% and 96.3%, respectively) were correctly classified. Overall, 90.7% of cross-validated grouped cases were correctly classified(Table 8).

Table 6. Predicting group membership based on standardized discriminate function coefficients

Variable	Coefficient
F1	0.896
F2	0.545
F4	1.073
F5	0.421
Eigenvalue	2.417
Correlation coefficient	0.841
Wilks' lambda	0.293
x^2	61.433**

** significant at .01

Table 7. Degree of representativeness of each National Park photograph

CNP	Score	CNP	Score	JNP	Score	JNP	Score
C611001	1.682	C816013	-0.781	J724002	-1.907	J801021	-1.802
C611026	2.255	C816019	-1.287	J724003	-2.275	J801026	-1.977
C611031	2.303	C816021	-1.767	J724005	-2.305	J801027	-2.152
C611035	2.886	C816038	1.984	J724006	-0.868	J801029	-1.671
C611038	2.049	C816043	2.598	J724007	-2.313	J801035	-1.994
C611053	1.327	C816056	2.805	J724009	-1.091	J802008	-1.472
C603001	1.905	C816095	-0.919	J724012	-2.255	J802009	-2.071
C603003	2.247	C816099	0.154	J724013	-0.993	J802010	-1.566
C603009	1.905	C816107	1.042	J801006	-0.719	J802011	-1.180
C603030	2.490	C915022	1.980	J801008	-1.663	J802012	-0.795
C603034	2.733	C915047	2.482	J801009	-0.974	J802013	-0.707
C603038	2.246	C915051	1.992	J801010	-1.724	J802054	-0.946
C603044	2.297	C915061	0.691	J801014	-1.433	J802056	-1.225
C501009	2.043			J801019	-1.304		

(a) Most Representative - Mar Lodge (b) Least Representative - Bridge of Dee

Figure 4. Representative landscape of the Cairngorms National Park based on low-level functions

(a) Most Representative - Samsinbong (b) Least Representative - Chotdaebong

Figure 5. Representative landscape of the Jirisan National Park based on low-level functions

Table 8. Correctiveness of group classification

Group	Predicted Group Membership		Total
	CNP	JNP	
CNP	23 (85.2%)	4 (14.8%)	27 (100.0%)
JNP	1 (3.7%)	26 (96.3%)	27 (100.0%)

DISCUSSION

Discussion concentrates on the importance of low-level functions of content-based image retrieval(CBIR) that are related to the delineation of natural landscape between the Cairngorms National Park in Scotland and the Jirisan National Park in Korea. This study verifies that relatively fewer factors making visual landscapes were effectively used to classify natural landscapes of the National Parks which had different semantics. Recognition of natural landscape is certainly based on the visual capacity of humans, although the classification of it can mostly depend on the semantic meaning. Viewers to the National Park often do not have an *a priori* idea of what specific landscape components are in the Park. So, the classification of natural landscape over cultures mostly depends upon one's abstract concepts, which are quite complex and sometimes vague.

However, it can be assumed that landscape of the National Park involving cultural meaning would also be classified by visual elements from a view-point of low-level functions of CBIR. Simple and efficient pattern recognition techniques for image classification based on low-level function simplify the procedure of landscape assessment. As the Jirisan National Park has an unique meaning to Korean, the Cairngorms National Park also has unique semantics to British. It determines cultural characteristics and makes possible to classify landscapes. In the same manner, landscape features determine unique visual characteristics in the National Park, which enables to classify between landscape of the Jirisan National Park and those of the Cairngorms National Park. Texture, shape, and color were proposed as the low-level functions of landscape photographs for discrimination. To do so, the feasibility of measuring visual elements for the reliable classification of landscape images was demonstrated. A linear discriminant boundary subsequently revealed effectiveness in classifying visual landscapes between two National Parks.

Natural landscapes of both National Parks were significantly represented by five visual factors in photographs: 1) near region-related factor, 2) middle region-elated factor, 3) water region-related factor, 4) far region-related factor, and 5) color of sky. Considering that any landscape photograph was characterized by the measurements of five visual factors, discriminant analysis could describe the difference between two landscapes photographs, and could show how different both landscapes were and which element was the most significant in differentiating landscapes. The results showed that both far region and near region had sufficient discrimination power for landscape classification between the Cairngorms NP and the Jirisan NP. Using the discriminant score, the best representative landscape of each National Park was identified respectively. The most distinctive characteristics in natural landscapes between two National Park was found from a texture difference in landscape photographs. The far region of the Cairngorms NP landscape was mostly not covered by trees, whereas that of the Jirisan NP was covered by trees. Same as the far region, the near region of the Cairngorms NP landscape was mostly not covered by trees, whereas that of the Jirisan NP was covered by trees. Compared with the Jirisan NP landscape, in brief, the Cairngorms NP landscape showed an open landscape that was mostly covered by heather, grass, or soil.

Although this study follows Shafer *et al.*,(1969)'s suggestion to demarcate landscape elements, other visual factors are possible. Classification of the landscape segments within a photograph does not have an exact criterion for implementation and so ambiguities may arise. Researchers would be impeded by the method of their measurement, even if more possible visible landscape elements can be elicited. Using a principal component analysis to reduce the explanatory variables can also be considered. Although reduced variables successively explain much of the other independent variables, some information from an application of all variables certainly is lost. Representing each National Park by a relatively small number of photographs seems to oversimplify the whole landscape of each National Park, although landscape photographs of both the Cairngorms NP and the Jirisan NP were taken throughout the main foot-paths of the whole National Park region, and selected by the actual viewers who well understood their typical landscapes.

In spite of its limitations, this study has useful implications for landscape researches. This study makes it possible that aesthetic preference for natural landscape would be evaluated on the low-level functions of landscape photographs and be subsequently compared over different cultures. The objective characteristics of visual landscapes such as shape, texture, and color are often used as independent variables of psychophysical paradigm in landscape preference modelling(Zube *et al.*, 1982; Daniel and Vining, 1983). In evaluating landscape preferences, psychophysical paradigm introduces various external elements (i.e. visual stimulus) into the landscape preference function. The goal of psychophysical approach is to develop models that provide accurate and reliable predictions of public perceptions of landscape quality based on objective measures of the physical features of the landscape. To do so, observer samples are taken from the general public, and the selection of samples is usually by convenience rather than by a formal random-sampling procedure. The psychological response is usually either scenic beauty or landscape preference. Relevant landscape variables may be defined in photographic terms, such as areas of a picture covered by vegetation, water, and sky.

The psychophysical approach has been examined and extended by the use of statistical techniques to verify the mathematical relationships between landscape elements and the scenic preferences of observers, because the approach has specific advantages in evaluating landscape preferences. A measure of preferences using the psychophysical model is useful for designing landscapes, especially in the steps of participatory procedures. A visual expression method is important for participatory planning to inform management techniques in order to make an aesthetically sound shape of the natural environment. This visual experience could give direct intuition to participants. In addition, aesthetic preferences could be increased or decreased through artificial manipulation of natural landscape in the psychophysical model. Therefore, using the psychophysical model, we are able to measure marginal preferences according to the alteration of proportion of landscape elements.

In terms of landscape preferences by the public, likewise, the low-level functions of landscape photographs used in this study suggest importance of managing skylines in landscape composition of the National Park. A far distant region composing skylines in a photograph is the most important factor to delineate natural landscape between different cultures. It means that landscape identity of the National Park over cultures is revealed by skylines in a most effective way. Hence, landscape designer or planner should be aware of the visual effect of far distant region of National Park landscape as well as near distant region, which will be helpful to promote the conservation of landscape identity of the National Park. Furthermore, this also implies that landscape restoration should be prudently processed because physical change of typical landscapes within a certain culture simply into more preferred forms could impair the social and cultural characteristics of landscapes.

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