大阪公立大学 Osaka Metropolitan University 学術情報リポジトリ

<Original Paper>Applications of Artificial Neural Networks to the Aesthetic Evaluation of Structures

メタデータ	言語: eng
	出版者:
	公開日: 2009-08-25
	キーワード (Ja):
	キーワード (En):
	作成者: KUDO, Yosuke, KUWABARA, Takao
	メールアドレス:
	所属:
URL	https://doi.org/10.24729/00009692

Sci. Rep. Coll. Agric. Osaka Pref. Univ. 51 : 7 ~13, Original

Applications of Artificial Neural Networks to the Aesthetic Evaluation of Structures

Yosuke KUDO and Takao KUWABARA
(Laboratory of Environmental Development Engineering, College of Agriculture, Osaka Prefecture University)

Abstract

A suitable aesthetic evaluation is an indispensable part of designing structures. However, it remains difficult for most engineers to design structures while reflecting aesthetic considerations due to their subjective nature. In order to reduce the burden of design, it is desirable to develop a technique which can support aesthetic evaluations. The present study provides the artificial neural networks approach for various aesthetic evaluations of structures, in particular concrete gravity dams. It has been found that the trained networks perform well. In addition, the relationship between the input and the output items has been identified quantitatively by a sensitivity analysis after training.

Key Words: aesthetic evaluation, artificial neural networks, concrete gravity dam

Introduction

Aesthetic considerations have recently been regarded as an indispensable part of designing structures (Hasegawa, Kudo and Ishii, 1995a). However, it remains difficult for most engineers to design structures while reflecting aesthetic considerations due to their subjective nature. In the case of large-scale structures, such as concrete gravity dams in particular, complicated considerations are required because these structures are public works. The primary considerations in the design of public structures must be safety and efficiency. Nonetheless, it is desirable to design them in such a way that they do not detract from the aesthetic quality of their locations. Because of the mechanical properties of structures such as dams, free-style designs are not as accessible as in the case of bridges, for example.

It is difficult to incorporate both practical and aesthetic factors in the actual design of structures because of the subjective nature of the latter. In order to reduce the burden of design, the introduction of computers into aesthetic considerations is recommended. Based on the diagram of aesthetic communication (Bense, 1969), the aesthetic phenomenon of structures is shown in Figure 1. The objective of this study is to provide the methodologies for computerizing an aesthetic evaluation which corresponds to the right side of Figure 1. The aesthetic evaluation is the most subjective problem of any aesthetic consideration. The artificial neural networks (ANNs) approach is well-suited to problems which are difficult to quantify, such as aesthetic evaluations.

The purpose of this ANNs system is to extract the aesthetic factors characterizing the appearance of a structure and to use them to generate indices which reflect the aesthetic evaluation. The relation between these factors and the aesthetic evaluation is vague, and therefore is, difficult to consider in a quantitative way. For this purpose, ANNs are applied which are well-suited to the problem of obtaining quantitative relationships between variables

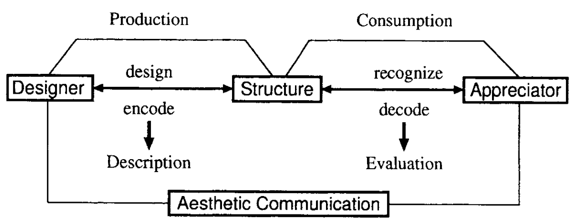

Fig. 1. Diagram of aesthetic communication.

in the absence of a theoretical model, i.e., an equation.

In this paper, concrete gravity dams have become the subject of an aesthetic evaluation. The following three aesthetic evaluation problems have been posed: the evaluation of the aesthetic impression of structures, the judgment of various compositions (viewpoint fields) and the prediction of actual reactions to the design concepts.

Artificial neural networks

Artificial neural networks (ANNs) are information processing systems which are based on the connectionist theory. ANNs do not really solve problems in a strictly mathematical sense, but they provide one method of obtaining approximate relationships between variables in the absence of a theoretical model, i.e. an equation. Therefore, ANNs are ideal for dealing with problems which do not have unique and mathematically precise solutions. In the present paper, the most widely used algorithm, the back-propagation neural network, is adapted for computing the indices of an aesthetic evaluation for structures. The following introduces the basic architecture of a standard back-propagation network which is described in detail in the References (Asou, 1988 ; Amari and Mukaidono, 1994).

A back-propagation processing unit transfers its inputs as

$$o^k{}_i = f\left(\sum_j w^{k-1}{}_j{}^k{}_i \; o^{k-1}{}_j - \theta^k{}_i\right). \qquad (1)$$

The notations used are as follows: $o^k{}_i$ is the current output value of the ith unit in layer k and $w^{k-1}{}_j{}^k{}_i$ is the connection weight joining the jth unit in layer $(k-1)$ to the ith unit in layer k. θ is a threshold value added to the weighted sum. It is omitted in some cases, while in others it is considered to be the weight value whose corresponding input value is permanently set at 1. Transfer function f is taken as a hyperbolic tangent function in this study, namely,

$$f(x) = \tanh(x) \equiv \frac{2}{1+\exp(-x)} - 1. \qquad (2)$$

In training a back-propagation neural network, a measure of the difference between the network computed outputs o_i and the desired outputs d_i of the training examples is defined as

$$E = \frac{1}{2}\sum (o_i - d_i)^2. \qquad (3)$$

The aim of the training phase is to minimize E by modifying the connection weights. The learning algorithm used in the present study is as follows:

$$\Delta w^{k-1}{}_j{}^k{}_i = -\varepsilon \frac{\partial E}{\partial w^{k-1}{}_j{}^k{}_i} \qquad (4)$$

where ε is called the learning rate parameter. For the acceleration of back propagation, a momentum term is added to Equation(4), in other words,

$$\Delta w^{k-1}{}_j{}^k{}_i(t+1) = -\varepsilon \frac{\partial E}{\partial w^{k-1}{}_j{}^k{}_i} + \alpha \, \Delta w^{k-1}{}_j{}^k{}_i(t) \qquad (5)$$

where α is the momentum parameter and t represents the update epoch.

Problems for which ANNs are applied

In this paper, ANNs are set up and trained to learn the underlying relationships between landscapes (photographs), including a concrete gravity dam, and the various aesthetic evaluations of them. Some examples of photographs are shown in Plates 1−3. The current study attempts to apply ANNs for the following three problems.

(1) Subject-A

A Subject-A network aims to evaluate the aesthetic impression of structures, such as concrete gravity dams, by ranking (Subject-A(1)) or by adjectives (Subject-A(2)). The following fifteen adjectives are used in the latter, namely, oppressive, cubic, static, simple, luxurious, tasteful, feeling, hard, clean, unitary, open, natural, stable, familiar, and delicate. These adjectives are selected according to previous studies (Kudo and Hasegawa, 1997).

(2) Subject-B

The selection of a viewpoint field decides the visual impressions of structures. Therefore, it is

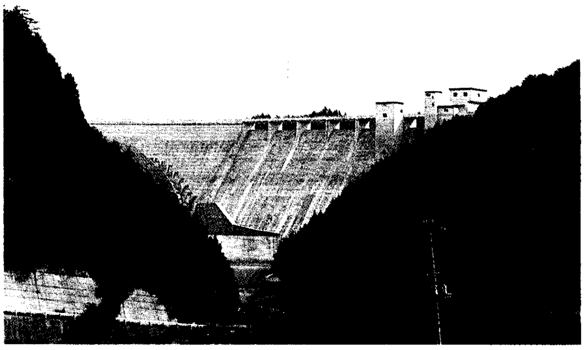

Plate 1. Nunome dam.

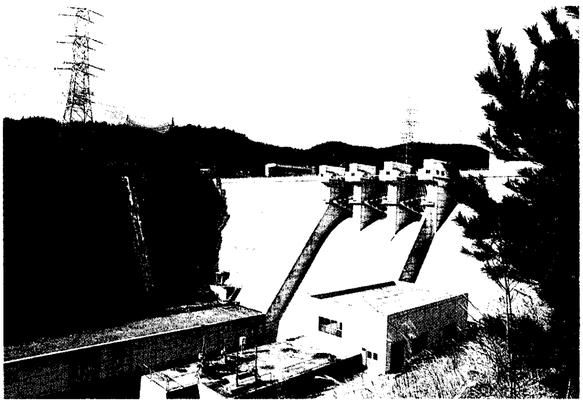

Plate 2. Ohkawase dam.

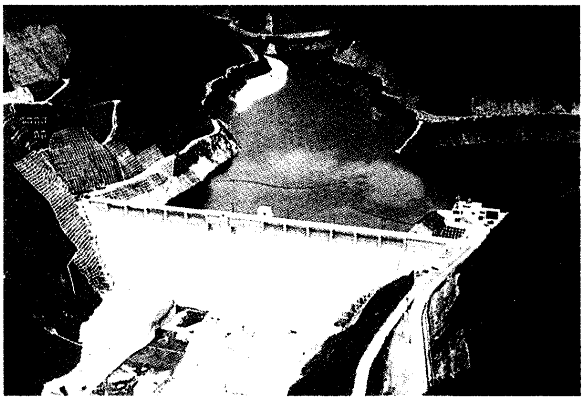

Plate 3. Kamuro dam.
(The Japan dam foundation, 1993)

important in the aesthetic design of structures to choose a suitable viewpoint field. A Subject-B network can judge various compositions by the following criteria: 'aesthetic favorite,' 'oppression,' and 'nature.' These criteria are widely used in aesthetic evaluations of concrete gravity dams. The networks are trained for the following four compositions of each structure (concrete gravity dams) in the present study: a) a medium-distance landscape with a centered dam body on the composition, b) a long-distance landscape with a centered dam body on the composition, c) a short-distance landscape looking up at the dam body, d) a close-distance landscape with centered upper structures on the composition. This classification of landscapes is according to Higuchi (1975).

(3) Subject-C

In order to design large-scale structures, such as concrete gravity dams, while reflecting aesthetic considerations, it is indispensable to fix the design concepts. A Subject-C network predicts actual reactions to the design concepts fixed during the planning stage. In this paper, the following six typical design concepts are considered: 'harmony with the history and the culture of the district,' 'harmony with the natural landscape,' 'respect for the structural beauty,' 'usefulness,' 'peacefulness' and 'dignity.' These design concepts are very frequently used in the aesthetic design of concrete gravity dams.

Training data

In training ANNs for a specific problem, a set of training data which can characterize the problem is required. Each set of training data is made by combing the input and the desired output data as in Table 1. Due to a recall process, data for the Ohkawase (Subject-A), dat for the arbitrary composition of each dam (Subject-B) and the Kamuro (Subject-C) dams have been excluded from the data sets, respectively. The following section introduces details on these items.

(1) Inputs

The input items are selected to reflect the aesthetic properties of the photographs, as shown in Table 1. The "artificial part" means the part which is occupied by structures other than the dam body. Each item in Table 1 ("whole," "dam body" and so on), excluding the "aesthetic measure of color harmony" and the indices of the visual structures of landscapes ("angle of horizontal vision," "distance," and so on) is an area occupied in a photograph. All items can be measured from all adopted compositions (photographs).

The effects of color harmony and the visual structure of landscapes have a great influence on the aesthetic evaluation (Hasegawa and Ku-

Table 1. Training data set

	Subject-A (1)	Subject-A (2)	Subject-B	Subject-C
Inputs				
1	dam body : whole		dam body : whole	dam body : whole
2	artificial part : whole		artificial part : whole	artificial part : whole
3	(artificial part + dam body) : whole		plant : whole	(artificial part + dam body) : whole
4	training wall : whole		upper structure : whole	plant : whole
5	slope protection works (mold) : whole		gate : whole	sky : whole
6	slope protection works (spraying) : whole		training section : whole	cloud : sky
7	slope protection works (plant) : whole		sky : whole	angle of horizontal vision
8	upper structure : whole		cloud : sky	angle of vertical vision
9	gate : whole		angle of horizontal vision	angle of incidence
10	plant : whole		angle of vertical vision	angle of elevation / depression
11	withering part of plant : whole		angle of incidence	aesthetic measure of color harmony
12	(river + river-bed) : whole		angle of elevation / depression	
13	sky : whole		distance	
14	reservoir : whole		aesthetic measure of color harmony	
15	width of gate : crest length of dam			
16	width of training wall : crest length of dam			
17	base length of dam : crest length of dam			
18	max height of upper structure : crest length of dam			
19	height of dam : crest length of dam			
20	max height of upper structure : height of dam			
21	minimum height of upper structure: max height of it			
22	cloud : sky			
23	angle of horizontal vision			
24	angle of vertical vision			
25	angle of incidence			
26	angle of elevation / depression			
27	distance			
28	aesthetic measure of color harmony			
Desired outputs				
	Rank order	Successive categories	Rank order	Successive categories

do, 1995b). The methodologies for calculating these values are described simply in the following.

Aesthetic measure of color harmony

P. Moon and D. E. Spencer applied the aesthetic measure by G. D. Birkhoff to color harmony (Moon and Spencer, 1944a). According to Birkhoff, the aesthetic measure is defined by the equation

$$M = \frac{O}{C} \tag{6}$$

where O represents the number of elements of order and C is the number of elements of complexity. Evidently a high aesthetic measure can be obtained with a very simple design (small C), although still higher measures may be possible with a complex design which has a sufficiently orderly arrangement (large O).

In applying aesthetic measures to color harmony, the specific methods for evaluating order and complexity must be determined. The procedure for deciding them is described in the following. Munsell notation is used.

Complexity C is determined from

$$\begin{aligned} C = & \text{ (No. of colors)} \\ & + \text{(No. pairs with hue difference)} \\ & + \text{(No. pairs with value difference)} \\ & + \text{(No. pairs with chroma difference)} \end{aligned} \tag{7}$$

Order O consists of the elements O_H associated with three variables (hue, value, and chroma) (Moon and Spencer, 1944b) and the elements O_A associated with area balance (Moon and Spencer, 1944c).

Finally, aesthetic measure M is calculated by use of Equation(6), namely,

$$M = \frac{O_H + O_A}{C} . \tag{8}$$

Visual structure of landscapes

The visual structure of landscapes can be expressed effectively by some indices (Higuchi, 1975). In the present study, the viewpoint field is characterized by the following indices: angle of horizontal/vertical vision, angle of incidence, angle of elevation/depression, and distance. All these indices can be measured directly from photographs.

(2) Desired output

The output data are psychological scale values obtained by a questionnaire survey. The survey was conducted in accordance with accepted psychometric techniques in February of 1997. Two methods were employed, namely, the method of rank and order and the method of successive categories (Dunn-Rankin, 1983). One hundred people were queried in this survey. Most of them were students. The questionnaire was conjunct with photographs of existing dam, namely, Eigenji, Hitokura, Dondo, Ohkawase, Ohno, and Nunome (Subjects-A and B); Hyuga, Kamuro and Kanna (Subject-C). The photographs were obtained in such a way that the conditions were uniform so as not to introduce additional, unquantified factors.

Results

(1) General capabilities

A hidden layer of adequate size is very important for a good performance of the ANNs. It has been proved that standard back-propagation networks can approximate any measurable functions to any desired degree of accuracy with just one hidden layer of sufficient processing units. The number of processing units per layer was set by trial and error, as shown in Table 2. Three different initial weights were used at the beginning of the training process. The root mean square (RMS) errors after training two thousand times are shown in Table 3. Since there is not enough space to describe everything about the results of Subject-B, only the results of the Ohkawase dam will be introduced. It is clear from Table 3 that the networks converged very well in all cases.

In order to test the performance of the trained ANNs on previously unseen input data, the

Table 2. No. of processing units in each layer

	Subject-A		Subject-B	Subject-C
	(1)	(2)		
Input layer	28	28	14	11
Hidden layer	24	18	8	8
Output layer	1	15	1	6

Table 3. RMS errors after training

	(1)	(2)	(3)
Subject-A(1)	4.01×10^{-3}	9.87×10^{-4}	4.18×10^{-3}
Subject-A(2)	6.66×10^{-3}	3.06×10^{-4}	4.92×10^{-3}
Subject-B(Ohkawase)			
· aesthetic favorite	1.63×10^{-3}	1.29×10^{-3}	1.48×10^{-3}
· oppression	7.91×10^{-4}	1.32×10^{-3}	1.03×10^{-3}
· nature	1.10×10^{-3}	1.33×10^{-3}	1.52×10^{-3}
Subject-C	7.11×10^{-14}	3.20×10^{-14}	2.88×10^{-13}

Table 4. Results of recall tests

	(1)	(2)	(3)	Desired Value
Subject-A(1)	−0.91	−0.85	−0.93	−1.00
Subject-A(2)				
· oppressive	0.31	0.26	0.16	0.50
· cubic	0.35	0.39	0.30	0.00
· static	0.27	0.22	0.33	0.00
· simple	0.09	0.28	0.47	0.00
· luxurious	−0.31	−0.07	−0.25	−0.50
· tasteful	−0.07	−0.18	−0.12	0.50
· feeling	−0.35	−0.30	−0.46	0.00
· hard	0.24	0.31	0.24	0.50
· clean	0.22	0.15	0.13	−0.50
· unitary	−0.18	0.19	0.11	0.00
· open	−0.38	−0.06	−0.26	−0.50
· natural	−0.47	−0.25	−0.53	−0.50
· stable	0.39	0.29	0.16	0.00
· familiar	−0.03	0.24	−0.19	0.00
· delicate	0.02	−0.22	−0.03	0.00
Subject-B(Ohkawase)				
· aesthetic favorite	0.36	0.41	0.36	0.36
· oppression	0.20	0.11	0.11	0.15
· nature	0.03	0.04	−0.06	−0.09
Subject-C				
· harmony with the history and the culture of the district	−0.40	−0.48	−0.35	−0.50
· harmony with the natural landscape	−0.22	−0.15	−0.18	0.00
· respect for the structural beauty	0.37	0.29	0.50	0.50
· usefulness	0.24	0.39	0.27	0.50
· peacefulness	0.00	0.17	0.00	0.00
· dignity	0.00	0.00	−0.03	0.00

recall tests were conducted on the testing data, i.e., the Ohkawase dam (Subject-A), an arbitrary composition (Subject-B), and the Kamuro dam (Subject-C). Except for a few cases (Subject-A(2) 'feeling' etc.), it can be seen from Table 4 that the tendency of the calculated psychological scale values resemble the tendency of the experimental results. It is thought, therefore, that these trained networks have the capability to provide a so-called generalization.

(2) Sensitivity analysis

After successful training, the ANNs are believed to have encoded the relationship between the input and the output vectors in a final set of connection weights. However, it is not always easy to interpret resulting weight states. No general trends regarding weight states can be deduced by a simple inspection, since all the weights and biases are interrelated. In other words, the effect of one input value on the output is difficult to analyze. By taking a partial derivative, it is possible to compute the sensitivity of the output value with respect to one of its input variables (Kudo and Hasegawa, 1995).

From Equation(1), the partial derivative of an output with respect to an input, in the case of the three-layer feed-forward network, is

$$\frac{\partial o^k{}_i}{\partial i^1{}_n}=\frac{\partial o^k{}_i}{\partial i^k{}_i}\cdot\frac{\partial i^k{}_i}{\partial i^1{}_n}$$
$$=f'(i^k{}_i+\theta^k{}_i)\cdot\sum_j\left(w^{k\text{-}1}{}_{jk_i}\frac{\partial o^{k\text{-}1}{}_j}{\partial i^1{}_n}\right)$$
$$=f'(i^k{}_i+\theta^k{}_i)\cdot\left\{\sum_j w^{k\text{-}1}{}_{jk_i}\cdot f'(i^{k\text{-}1}{}_j+\theta^{k\text{-}1}{}_j)\cdot w^{k\text{-}2}{}_{m^{k\text{-}1}j}\right\}. \quad (9)$$

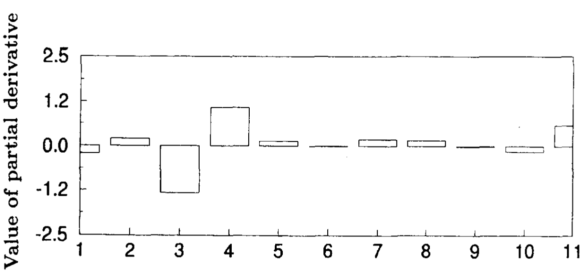

Fig. 2. Result of sensitivity analysis (Subject-C: harmony with the natural landscape).

When $k=3$, it is deduced from Equation(9) that

$$\frac{\partial o^3{}_i}{\partial i^1{}_n}=\frac{1-(o^3{}_i)^2}{2}\cdot\sum_j\left\{w^2{}_{j^3 i}\cdot\frac{1-(o^2{}_j)^2}{2}\cdot w^1{}_{n^2 j}\right\}. \quad (10)$$

An example of the partial derivatives for the trained networks are shown in Figure 2. The number of horizontal axes corresponds to the number in Table 1. What is evident from this figure is the effect each input item has on the output value. For example, it can be seen from Figure 2 that the item "plant : whole" has a positive effect on the aesthetic evaluation in regard to harmony with the natural landscape, while that the item "(artificial part+dam body) : whole" has a negative effect on it. In this way, the input items that have the most effect on the aesthetic evaluation can be identified. The results of the sensitivity analysis provide guidelines for the actual aesthetic design.

Conclusion

In this paper, a technique for the aesthetic evaluation of concrete gravity dams which employ ANNs has been introduced. ANNs have been applied for three problems, i.e., the evaluation of the aesthetic impression of structures, the judgment of various compositions (viewpoint fields), and the prediction of actual reactions to the design concepts. In this approach, the training data sets have been generated by combining the results of a questionnaire survey and the input items which reflect the aesthetic properties of the appearance. The questionnaire was conducted in accordance with accepted psychometric techniques.

These are powerful methods for providing indices which reflect aesthetic evaluations. ANNs are found to be useful for finding the underlying relationship between the appearance and the aesthetic evaluation of it. ANNs act as a transfer function with the appearance indices as input and the aesthetic evaluation as output. An added benefit of the proposed approach is that the trained networks can be improved continuously by learning from new training data sets.

The effects of network configurations were also examined to get the best results. The trained ANNs have been tested with previously prepared testing data. It was found that the trained networks perform well. The input items that have greater influence on the output can be identified quantitatively after training them through a sensitivity analysis.

The training of ANNs is a simple process. If only a suitable training data set were prepared, the networks which adapt for various problem solving techniques would be developed. However, ANNs are training data dependent, so preparing a good training data set is the most important issue in the use of ANNs. More sophisticated models will be introduced in future studies. Nevertheless, the basic concepts of problem formulation and network training outlined in this paper should be the same.

ANNs have flexibility in the representation of such vague information as aesthetic sense, and this flexibility provides considerable power. It is expected that the approach provided in the current study will contribute to a reduction in the difficulties related to the aesthetic design of structures.

Acknowledgment

The authors wish to thank Professor T. Hasegawa for his helpful comments and encouragement on this work. Thanks are also due to Mr. Yahagi (Kubota) for his assistance with the computational work.

References

Amari, S. and Mukaidono, M. (Ed.) 1994. Neuro and Fuzzy. Baifukan, 275 p. (in Japanese)

Asou, H. 1988. Neural Network Data Processing. Sangyo-Tosho, 198 p. (in Japanese)

Bense, M. 1969. Einführung in die informationstheoretische Ästhetik. Rowohlt Taschenbuch Verlag, 147 p.

Dunn-Rankin, P. 1983. Scaling Methods. Lawrence Erlbaum Associates.

Hasegawa, T., Kudo, Y., and Ishii, M. 1995 a. A study on quantitative aesthetic evaluation for concrete gravity dam by artificial neural networks. Trans. of JSIDRE, **179**, 583-589. (in Japanese).

Hasegawa, T. and Kudo, Y. 1995 b. A study on quantitative aesthetical evaluation system for concrete gravity dam using artificial neural networks. *In* "Proc. The MWA Int. Conf. on Dam Engineering," 283-287.

Higuchi, T. 1975. The Visual and the Spatial Structure of Landscapes. Gihou-dou, 168 p. (in Japanese)

Kudo, Y. and Hasegawa, T. 1995. Application of artificial neural networks to aesthetic design by conducting sensitivity analysis. *In* "Proc. 52 nd Kyoto Branch of JSIDRE Annual Conf.," 58-59. (in Japanese)

Kudo, Y. and Hasegawa, T. 1997. Quantification of KANSEI-information including aesthetic evaluation problem for concrete gravity dams. *In* "Proc. JSIDRE Annual Conf.," 524-525. (in Japanese)

Kudo, Y. and Hasegawa, T. 1998. Information processing approach to aesthetic design for structures. *In* "Proc. JSIDRE Annual Conf.," 778-779. (in Japanese)

Moon, P. and Spencer, D. E. 1944 a. Aesthetic measure applied to color harmony. J. Opt. Soc. Am., **34** (4), 234-242.

Moon, P. and Spencer, D. E. 1944 b. Geometric formulation of classical color harmony. J. Opt. Soc. Am., **34** (1), 46-59.

Moon, P. and Spencer, D. E. 1944c. Area in color harmony. J. Opt. Soc. Am., **34**(2), 93-103.

The Japan dam foundation. 1993. The Dam Digest, **589**,p.4.

(Recieved Mar. 1, 1999; Accepted Mar. 30, 1999)