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Designing of Realizable Luminous Intensity Distributions with Hopfield Neural Networks

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1. Introduction

Since the Hopfield Neural Network [1] first appeared, many applications and subsequent developments of this type of network have been carried out. The neural network has proven successful regarding such issues as the Traveling Salesman Problem [2]. This paper focuses on the development of a lighting design system based on a property of the Hopfield Neural Network: that energy evolves toward a minimum value.

Considering an environment with a given luminance distribution, we solve an inverse problem of lighting design. In other words, taking into account interreflective light, the proposed system finds a luminous intensity distribution of light sources that creates the illumination designed by the user.

Initially, the system receives a luminance distribution specified by the user. The data is then processed by the first process of a Hopfield Neural Network, resulting in a sketchy luminous intensity distribution, called a "sketch lamp". The "sketch lamp" may not be available or simply may not exist in the industry. The "sketch lamp", therefore, is input in the second process. Each process uses a Hopfield neural network with different objective functions in an attempt to determine the optimal and realizable luminous intensity distribution (see Fig. 1)

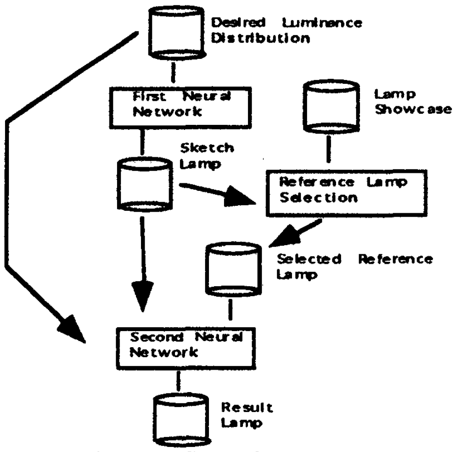

Figure 1: flow of the system

2. Objective Functions and Hopfield Neural Networks

In the first process, the system calculates luminous intensity distributions of light sources that realize the specified luminance distribution.

The objective function of the first process can be expressed as:

$$O=\sum_{i=1}^{m}(Q_i-B_i)^2, \tag{1}$$

where Q_i is the individual value of the desired luminance distribution (considering that the entire environment is divided into discrete pieces), B_i refers to the luminous energy that leaves a surface and m is the number of patches (discretized pieces). The luminous energy from patch i consists of self-emitted light (E_i) and reflected light, and the radiosity of each patch is expressed as

$$B_i=E_i+\rho_i\sum_{j=1}^{m}B_jF_{ij}, \tag{2}$$

where ρ_i is the reflectivity of patch i and F_{ij} is a form factor determined by the geometry between two patches i and j. An equation relating luminance and luminous intensity distributions is given by:

$$E=H\ V, \tag{3}$$

where V represents the discretized luminous intensity distribution and H is a matrix determined by the geometry of the light sources and the patches. From Eqs. 2 and 3 it is possible to determine that:

$$B=A\ V, \tag{4}$$

where A is a matrix determined by the geometry of the light source and the patch.

The Energy equation of the Hopfield Neural Network can be written as[1]:

$$E=-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}T_{ij}V_iV_j-\sum_{i=1}^{n}I_iV_i\ . \tag{5}$$

To construct a Hopfield Neural Network that most optimizes the objective function, Eq. (4) is substituted into Eq. (1), and the objective function is modified in the format of Eq. (5). The weight **T** and bias **I** can be expressed as:

$$T_{jk}=-2\sum_{i=1}^{m}a_{ij}a_{ik},\quad I_j=2\sum_{i=1}^{m}Q_ia_{ij}. \tag{6}$$

The result of the first process is the sketch lamp, which is then input in the second process to get a realizable luminous intensity distribution. The idea here is to approximate the sketch lamp to a lamp in a showcase (reference lamp), where several kinds of luminous intensity distributions found in daily life are evident.

In the second process, the system first searches over the lamp showcase to find the luminous intensity distribution that is most similar to the sketch lamp. At this point, the system also calculates the scale factor f,

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which is used for compensating the difference between the selected luminous intensity distribution from the showcase and that of the sketch lamp.

The objective function for the second process is expressed by:

$$O=\sum_{i=1}^{m}\left(Q_i-B_i\right)^2+K\sum_{i=1}^{n}\left(fR_i-V_i\right)^2, \qquad (7)$$

where K is a parameter controlling the similarity of the luminous intensity distribution to that of a lamp in the showcase, R_i and V_i express the selected luminous intensity distribution from the showcase and the luminous intensity distribution of the sketch lamp, respectively. The second term of the objective function refers to the search for a luminous intensity distribution that is as close as possible to a realizable luminous intensity distribution. From Eqs. 5 and 7, the Hopfield Neural Network in the second process consists of the following weight and bias:

$$T'_{jk}=\sum_{i=1}^{m}-2a_{ij}a_{ik}-2K\delta_{jk}, \quad \delta_{jk}\begin{cases}0 & \text{if } j\neq k\\ 1 & \text{if } j=k\end{cases} \qquad (8)$$

$$I'_j=2\sum_{i=1}^{m}Q_i a_{ij}+KfR_j \qquad (9)$$

3. Results

A two-dimensional model room whose walls' reflectivity is 0.6 is applied to the proposed system. The room is divided into 40 discrete pieces (patches) and desired luminances are specified for each patch as shown in Fig. 2 (a). The sketch lamp from the first Neural Network and the luminance distribution due to the sketch lamp are depicted in Fig. 2 (b). The sketch lamp is then compared to the reference pattern in the showcase (Fig. 2 (c)), and the closest luminous intensity is then chosen (reference lamp E). Using the closest lamp, the second Neural Network is executed. Fig. 2 (d) depicts the final result obtained from the second Neural Network solution.

4. Conclusion

We proposed a method of finding luminous intensity distributions of light sources when specifying a desired luminance distribution, taking into account interreflection of light. To solve the inverse lighting design problem, Hopfield Neural Networks with different objective functions were employed. We applied the method to a two-dimensional model and demonstrated the usefulness of the proposed method. The proposed method can also be extended to three dimensions.

References

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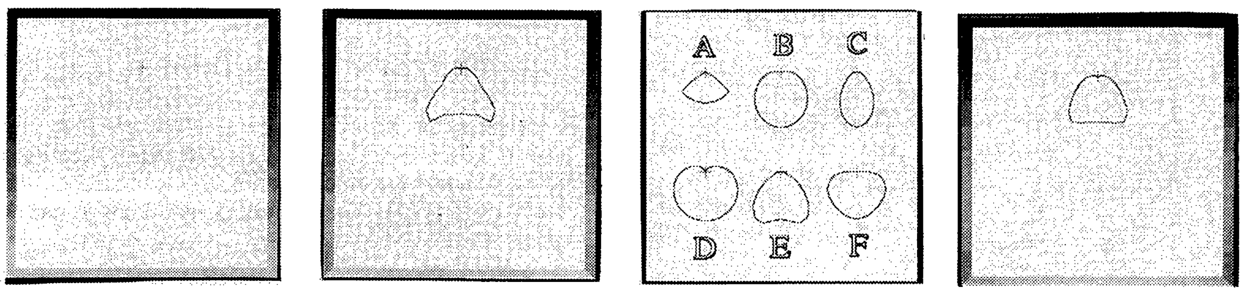
[3]Takahashi K, Kaneda K, Yamanaka T, Yamashita H, Nakamae E, Nishita T (1993) Lighting Design in Interreflective Environments using Hopfield neural networks, Journal of Light & Visual Environment, vol. 17, no. 2, pp. 9 - 15



(a) desired luminance (b)sketch lamp (c)showcase (d)final result

9 19 [cd/m]

Figure 2: Application of the method to a two-dimensional room