Radiosity and Hopfield Neural Networks applied to Inverse Lighting Design: initial attempts in 3D

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Abstract

This technical communication describes the employment of a new method that gathers radiosity and the Hopfield Neural Network applied to the task of designing the lighting of a closed space and considering interreflection of light. The proposed method finds the best luminous intensity, according to a showcase of realizable luminous intensities that are passive of being produced by the industry or be available in the market. Partial results of the algorithms applied to the lighting of 3D environments are presented.

1. Introduction

The use of a neural network as a tool to solve problems in Computer Graphics has been already termed as neurographics [(Kin et al. 1992)] and is an asset of the multi disciplinarity that characterizes many of the research conducted in recent years.

The authors of this work [(Takahashi et al. 1993)] introduced a new method for finding an adequate luminous intensity to a certain environment, taking into account the inter reflectivity of the environment and the realizability of such luminous intensity distribution.

A traditional or direct approach to design the lighting of an environment, using computer graphics, would be described as a cycle of edit-render, i.e., the designer set the light positions, the interaction of the light source and the environment is calculated, rendered and displayed, in the case the result does not fit the desired goals, this process is repeated. An inverse approach [(Cohen 1994)] would be thought as given a desired luminance distribution, the system would go backwards and find the luminous intensity that gives origin to that particular luminance distribution and furthermore the procedures would care for the existence of that luminous intensities.

2. Theoretical aspects of the method

The problem of obtaining a luminous intensity, given a desired luminance distribution can be viewed as an optimization problem, characterized by objective functions or the energy equations of the Hopfield neural network [(Hopfield 1982)] to be solved.

The first objective function to be solved can be expressed as:

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

where Q_i is the individual value of the desired luminance distribution attributed to each patch, B_i refers to the total luminous energy that leaves patch i consisting of self-emitted light (E_i) and reflected light ($\rho_i \sum_{j=1}^{m} B_j F_{ij}$). The radiosity [(Goral et al. 1984)] of each patch is:

$$B_i = E_i + \rho_i \sum_{j=1}^{m} B_j F_{ij}, \qquad (2)$$

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

$$\mathbf{S} = \mathbf{HV} \qquad (3)$$

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:

$$\mathbf{B} = \mathbf{AV} \qquad (4)$$

where **A** is a matrix determined by the geometric relationships between the light sources and the patches. The Energy equation of the Hopfield Neural Network [(Hopfield 1982)] can be written as:

$$E = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} T_{ij} V_i V_j - \sum_{i=1}^{n} I_i V_i \qquad (5)$$

where **T** is a matrix related to the weight between two neurons, **V** is the set of neurons, and **I** is the bias. 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** for the first objective function can be expressed as:

$$T_{jk}=-2\sum_{i=1}^{m} a_{ij}a_{ik},\ T_{jk}=-2\sum_{i=1}^{m} a_{ij}a_{ik} \qquad (6)$$

The result of the first neural network is termed sketch lamp, which is then input into a process of selection. Once one reference lamp is selected, the sketch lamp is then input into a second Hopfield neural network. The idea here is to approximate the sketch lamp to a reference lamp in a showcase. The showcase contain several kinds of luminous intensity distributions found in daily life.

The objective function for the second process is expressed by:

$$O=\sum_{i=1}^{m}\left(Q_i-B_i\right)^2+\psi\sum_{i=1}^{n}\left(f_\ell R_{\ell i}-V_i\right)^2 \qquad (7)$$

where ψ is a parameter controlling the similarity of the luminous intensity distribution to that of a lamp in the showcase, f_ℓ is the scale factor that compensates the difference between the selected luminous intensity distribution and that of the sketch lamp. $R_{\ell i}$ and V_i expresses the selected luminous intensity distribution (ℓ) from the showcase and the luminous intensity distribution of the sketch lamp, respectively. From Eqs. 5 and 7, it is obtained the weight (T) and the bias (I) for the second Hopfield neural network are:

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

$$I'_j=2\sum_{i=1}^{m}Q_ia_{ij}+\psi f_\ell R_{\ell j} \qquad (9)$$

3. Experimental Results

Initially a 3D room was modeled, dimensions 4.0 [m] x 5.0 [m] x 3.0 [m], where the coefficient of reflectivity are: 0.7 for the ceiling, 0.5 for the walls and 0.3 for the floor. The **Q** matrix, i.e., the desired luminance distribution for the room is chosen to be a luminance distribution caused by a punctual light source positioned at the center of the room and 2.0 [m] above the floor. Fig.1 depicts the desired luminance distribution, measured in [cd/m^2], attached is the color table of the luminance distribution. Fig.2 shows the room subdivided into patches, in this example, the number of patches are 442. Fig. 3 and 4 depicts the obtained luminance distribution, using a continuos and a discrete color table.

The selected lamp is the lamp A from the showcase depicted in fig.5.

4. Concluding Remarks

We applied a new method of finding realizable luminous intensities of light sources to 3 dimensional environments. The partial results obtained are promising. New tests are under design in order to test this method in its full extent.

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