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Deep Precomputed Radiance Transfer for Deforming Objects

Figure 1: *New EG Logo*

Abstract

Traditional Precomputed Radiance Transfer methods require a lot of memory to save the precomputed data for real time rendering. For an animation sequence such data would be gigantic. We proposed a deep learning precomputed radiance transfer framework (DPRT) for deforming object, saving only the weights of the network, which lowers the memory cost in orders of magnitudes. Object is first parameterized via harmonic mapping and reconstructed to form geometry and normal image as the inputs of a carefully designed fully convolutional network. (see http://www.acm.org/about/class/class/2012)

CCS Concepts

• ***Computing methodologies*** $\rightarrow$ *Collision detection;* • ***Hardware*** $\rightarrow$ *Sensors and actuators; PCB design and layout;*

1. Introduction

Rendering photo-realistic appearances entails solving the *Rendering Equation* for each point on an objects surface. This computation can be extremely demanding, especially considering global illumination effects where the problem becomes highly recursive.

Precomputed Radiance Transfer (PRT) is a technique addressed to overcome this computational overkill, simplifying the rendering equation but still enabling high-quality renderings for complex illuminations. The quintessence is to perform a single pre-computation step of the light-transport information and only evaluate the equation at runtime.

Classic PRT algorithms function well for static scenes; however, these are destined to fail eyeing dynamic and/or interactive environments, in which considered objects undergo significant deformations. Responsible is a term in the rendering equation called the *transfer function* T which is fully dependent on the shape of the surface. That is, any object deformation implies a re-computation of T, requiring expensive ray-casting. Hence, using classic PRT to render deformable objects would involve pre-computing large amounts of data, leading to immense storage consumptions.

On top of that, the costly and memory consuming pre-computation of these *transfer functions*, presumes knowledge of all future deformations of the regarded object. Nevertheless, dynamic or interactive scenes may require on-the-fly adaptive, previously unknown, object deformations. Examples of such are: interactive physically based deformations for cloth or soft-body simulations [find references] ; or more recently developed character animations that involve automatic on-the-fly pose adaptation [for instance, Holden paper, deepmotion,etc...].

We propose a Deep Learning framework addressed to overcome the limitations of traditional PRT algorithms described above. We call this approach *Deep Precomputed Radiance Transfer* (DPRT). In particular, we replace expensive ray-casting algorithms by a deep Convolutional Neural Network (CNN) that, for a given deformation, infers the corresponding set of SH - coefficients that represent the *transfer function*. Thus, regardless of the number of deformations our method maintains a constant size (fixed storage consumption). Moreover, due to the inherent generalisation capabilities of DNN's, DPRT is able to accurately predict appearances of previously unknown shapes.

The main contributions of our approach are:

- enabling arbitrary and adaptive deformations,
- while maintaining a compact representation.

2. Related Works

2.1. Precomputed Radiance Transfer

Precomputed Radiance Transfer was first proposed by Peter-Pike Sloan et al. [SKS02] to handle

2.2. Geometry Image

Geometry image [GGH02] is utilized to preserve 3D mesh as 2D image. The regular shape of these images could be used in different areas of graphics reseaches and applications. Such parameterization process could be done via different methods [GGH02, SBR16].

3. Method

In PRT the integrands of the *rendering equation*

$$L(\boldsymbol{x}, \boldsymbol{\omega}_0) = \int_{\Omega} L_{\varepsilon}(\boldsymbol{x}, \boldsymbol{\omega}_i) T(\boldsymbol{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_0, \boldsymbol{N})\, d\boldsymbol{\omega}_i, \tag{1}$$

are split into two terms:

1. The *lighting function*: $L_{\varepsilon}(\boldsymbol{x}, \boldsymbol{\omega}_i)$, describing all incoming radiance over the hemisphere around $\boldsymbol{x}$,
2. and the *transfer function* :

$$T(\boldsymbol{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_0, \boldsymbol{N}) = f(\boldsymbol{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_0) G(\boldsymbol{x}, \boldsymbol{\omega}_i, \boldsymbol{N})$$

describing the surface reflectance properties f (BRDF) and the geometric information G surrounding $\boldsymbol{x}$. Where $\boldsymbol{N}$ is the normal vector of the surface at $\boldsymbol{x}$.

Both functions L_{ε} and T are projected onto a suitable set of orthonormal basis functions, in our case *Spherical Harmonics* (SH), for faster evaluation.
For n number of SH bands and l_i, t_i being the i-th SH coefficient of L and T respectively, the rendering equation 1 reduces to [for more PRT SH, see citations]:

$$L(\boldsymbol{x}, \boldsymbol{\omega}_0) \approx \sum_{i}^{n^2} l_i \cdot t_i$$

Goal: The objective of our CNN is to directly predict the coefficients t_i's, for a given shape, skipping the costly ray-casting computations of G.

3.1. Object Reconstuction

To this end, the network has to be fed with shape information. This information lies intrinsically on a non-Euclidean domain on which the convolution operation is not well defined [MBBV15, BBL*16, MGA*17]. We chose a parametric approach called *Geometry Image* which translates the problem into a space on which standard CNNs can be applied [GGH02, SBR16].

(see Figure 2 picturing input and output of network).

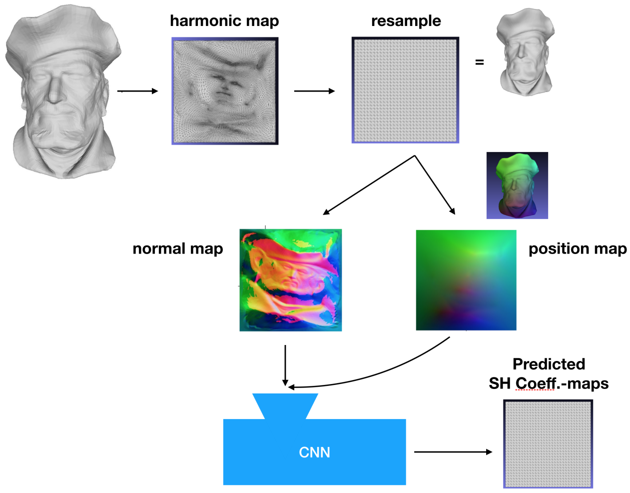

Figure 2: *Just an example...(TODO: better picture)*

3.2. DPRT

4. Results and Comparisons

4.1. DPRT on Diffuse Object

4.2. DPRT on Glossy Object

5. Future Work

- Use stretch-minimizing parametrization of paper [GGH02] instead of current harmonic mapping.
  → paper claims: more uniformly distributed
- extend parametrisation to surfaces with higher genus

References

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