Deep Volumetric Ambient Occlusion

(Comprehensive Summary)

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Keywords: Direct Volume Rendering (DVR), Global Illumination (GI), Neural Network (NN), Convolutional Neural Network (CNN), Deep Volumetric Ambient Occlusion (DVAO), Deep Learning (DL).

I. Objective

Through this work, the authors introduce a NN based learning for volumetric illumination through various modalities. They propose strategies to train 3D CNNs to enable them to compute volumetric ambient occlusions, by focusing on the transfer function.

II. Contributions

The outline of the contributions are:

1) Introduction of novel DVAO to predict volumetric ambient occlusions in DVR using 3D CNNs.
2) Strategies to apply CNN on unstructured information, focusing on the transfer function
3) Evaluation of DVAO and its generalization beyond their specific application.
4) Layout of guidelines for the application of CNNs in volumetric visualization.

III. VIS Designs / Techniques Used

They visualize the volumetric and occlusion information through 3D rendering techniques, providing us with various snapshot images of the results, comparing them with the ground truth and traditional algorithms.

IV. ML Methods Used

They use CNNs to learn ambient occlusions, using various encoders and decoders. The input is the volume information of size 128^3x1, encoded to 1^3x512, and finally, the output is decoded 128^3x1 occlusion information. They use 2 different transfer functions described in the paper. They also describe the injection strategies for the data passed through the transfer functions in detail. They train their model in a supervised learning method using stochastic gradient descent and define the loss function for their method. They also compare their evaluation to traditional benchmark algorithms like LAO-190 and LAO-32.

V. Strengths

1) Through their novel work on DVAO, the authors detail the application of CNNs on DVR for ambient occlusions as one of the initial works.
2) Their module can be easily integrated with the existing information using a simple texture lookup.
3) When it catches up to the performance metrics of traditional algorithms, this method will be faster in inference once trained.
4) Their use of implicit representation makes computation easier because the transfer function is not applied on the top of the illumination task.

VI. Shortcomings

1) They represent their work on low-resolution volumes of the size 128^3x1 due to computational constraints. The number of parameters of CNN explodes as the dimensions of the volume increase.
2) Their method, being one of the early works, is still behind in accuracy compared to traditional methods, and results are often in disagreement with the ground truth.
3) While using implicit representation, the CNNs can't be trained on the raw data and features have to be generated before providing input.

VII. Future Work

The current method lacks in performance and accuracy when compared to traditional methods, but the authors hope that there will be future work on DVR and GI using DL. To increase the resolution of volumetric information, they hope to work with splitted volume sections in the future.

VIII. Question for Discussion

As the authors mention that they will work with splitted volume sections for better resolution, will the different volume sections hinder the ambient occlusions of one particular section when processed independently? If so, can this be resolved with an additional DL model to learn spatial orientation?

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