

CS 550 -- Fall Quarter 2016

Paper Analysis Project

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Style Compatibility for 3D Furniture Models

Tianqiang Liu, Aaron Hertzmann, Wilmot Li and Thomas Funkhouser's titled "Style Compatibility for 3D Furniture Models", which proposes a way to learn a metric for stylistic compatibility between furniture in a scene. Style compatibility means different kinds of objects can fit each other well. So, in this paper mainly discuss about how to find a way to let 3D furniture models fit each other very well. Modeling 3D scenes is one of the most common creative tasks in computer graphics, and there are large online repositories of 3D models provided to amateurs or automatic programs to create scenes. Many existing tools can help users to select the appropriate categories and placements of objects when modeling a 3D scene, however, most of them are ignore style compatibility, which make objects not fit each other harmony. So this paper is aim at developing a mathematical representation of style compatibility between objects, which can be used to guide 3D scene modeling tools better. More specifically, this paper focus on understanding how the geometry of 3D models affect their stylistic compatibility, not include other properties such as colors, materials, etc.

There are four authors cooperated with this paper, they are Tianqiang Liu, Aaron Hertzmann, Wilmot Li and Thomas Funkhouser. Tianqiang Liu and Thomas Funkhouser worked in Princeton University, and Aaron Hertzmann and Wilmot Li came from Adobe Research. Tianqiang Liu was a PhD Student and Research Assistant in Princeton University, now he is working for Google as a computer engineer. He is good at Computer graphics, Computer vision, Machine learning. He devoted on the algorithm that analyzes 3D scenes by parsing with a grammar learned from examples. In addition, he also did research intern in Adobe for 7 months, this paper is what he worded on during that time. Aaron Hertzmann is a Principal Scientist in Adobe Research, he focuses on Computer Graphics and Computer Vision. Aaron Hertzmann

received a BA in computer science and art & art history from Rice University in 1996, and a PhD in computer science from New York University in 2001. He was a Professor at University of Toronto for 10 years. He is an ACM Distinguished Scientist and IEEE Senior Member, and holds courtesy faculty appointments at University of Washington and University of Toronto. Wilmot Li is a Senior Research Scientist, also work in Adobe Research the same as Aaron Hertzmann. He got PhD from University of Washington, where he was a member of the Graphics and Imaging Laboratory, and used to be a research assistant in University of Washington. Thomas Funkhouser is a professor and director of graduate studies department of computer science of Princeton University, he devotes on Princeton Computer Graphics Group, he got ACM SIGGRAPH Computer Graphics Achievement Award (2014), Emerson Electric, E. Lawrence Keyes Faculty Advancement Award (2001), National Science Foundation Career Award (2000), Alfred P. Sloan Research Fellowship (1999). All in all, all of them are experts in computer graphic area, and devoted in 3D Modeling researcher for many years.

The first step of their research is to collect data for object compatibility using crowdsourcing. They focus on style compatibility rather than similarity. They gather compatibility preferences in the form of triplets (A, B, C). Each triplet represents a human evaluation whether reference object A is more compatible with object B or with object C. To gather triplets efficiently, they use the grid technique proposed by Wilber, which is that each task evaluates six target objects together with a reference object A, let the rater select 2 target objects that most compatible with A in a grid of six images, so that they let each response be converted to 8 triplets, one object that is selected, one object that is not selected, and the reference object. In this way, it is more efficient than asking the participant to pick the best between two. They collected their 3D furniture models for dining rooms and living rooms, and they collected some objects for dining rooms and living rooms in their experiments, then they randomly generated some different kinds of questions, and split the questions into two Human Intelligence Tasks. They make each HIT was done by 50 different participants. Then

they did analyze this data. The result is like subjective impression that each object in our data set contains just a few others for which it is strongly compatible or incompatible.

The next work they did is to define a feature vector x of geometric properties indicative of an object's style. Because of different object in the same class may have some subtle deviations from a common overall shape, they need to solve this challenging problem. They came up with a method that is to compute a consistent segmentation of all objects within the same class, compute geometric features for each part separately, and then represent each object by the concatenation of feature vectors for all its parts and its entire shape. Their implementation of this consistent segmentation method is based on the algorithm of Kim's "Learning part-based templates from large collections of 3d shapes". This algorithm can produce a consistent segmentation and labeling for all models.

After given the crowdsourced triplet data and the part-aware geometric features, authors also worked on a measure of compatibility between a pair of models from different object classes. They use a function $d(x_i, x_j)$ that scores compatibility, with lower values being more compatible. To solve this problem, they use a diagonal matrix, representing scaled Euclidean distance between feature vectors. In order to deal with heterogeneous furniture types, they propose to learn a separate embedding matrix W_c for each class c . so they got a distance function: $d(x_i, x_j) = \|W_{cix_i} - W_{cjsx_j}\|_2$. With several research, they came up with lots of functions to calculate the compatibility, in the end, they got a regularization, and implemented their algorithm in Python. They also did some test, and the test showed a very good result, the result of their method is better than the method of training on a subset of the triplets. Then they give us some utility of their compatibility metric in applications, which are shape retrieval, furniture suggestion, and scene building.

In the end, authors told us the result of their research is successful, their

quantitative results show that it is possible to learn a compatibility metric for furniture of different classes from these triplets, and their user studies show that the learned metric can be used effectively to achieve higher style compatibility in applications.

Furthermore, the authors also noticed some limitations of their research. First is they only consider a simple set of geometric features and can't detect fine-grained style variations, such as types of ornamentation. Second, they only work on geometric properties, they didn't consider materials, colors, construction methods, affordances, and other properties of 3D models, which are important properties of style compatibility. Third, it is targeted only at furniture within interior environments, whose styles have a rich history, but perhaps unique properties that do not extend to other object and scene types, this technique is important for future study in some other 3D modeling systems. So, in the future, these three parts of problems would be good subject to do further studies. Besides, these three problems they came up with, I think it is a very significant paper for 3D modeling researching. If I were a researcher, I would like to start working on color properties of style compatibility, and combine these two researches together. Split problem to small pieces and combine them together is a good way to solve a massive problem.

From this paper, I learned about ideas of comparing style compatibility of geometric properties. I learned that collecting data from crowdsourcing. In crowdsourcing, I can gather triplets by using grid technique, which is better than asking the participant to pick the best between two. In addition, I know the method to split the object to small part, and define a feature vector x of geometric properties indicative of an object's style. However, in this part, I only know the method they used, the algorithm they implemented I still need to read Kim's paper. Then, there is the most important part, how to calculate the compatibility between a pair of models. This part is the most difficult to understand, because of a mass of functions they used. This part is the soul of this paper. I also learned that machine learning in solving these problems is very significant. With a mass of data training the algorithm, computer can

give some accurate prediction for users. For the propose of this paper, they want to provide a better method for metric for stylistic compatibility, they did that it.