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Paper review: 2.5D Cartoon Models

This article present an approach to transfer cartoon objects and figures into 2.5D from 2D vector art drawing. The 2.5D cartoon models are easier to achieve than 3D models. Generating a 3D model is time-consuming, and some 2D drawings are not able to be reproduced in 3D model. The 2.5D structure associates every stroke of cartoon figures with a single three dimensional position, and can generate plausible rendering of the figures in new views by translating the strokes' positions in 3D, while interpolating their shapes in 2D. This simple 2.5D model structure allows rotations of cartoon objects, and only required 3 to 4 different views to be capable to generate plausible rendering of the cartoon objects in any direction. The final model would still be the 2D, while supporting full 3D rotation.

The advantage of this new approach is that it can render the cartoon characters in any angle. 2.5D cartoon models are able to render stylized, organic shapes such as heads, and also support a variety of stylized 2D drawing effects. Animation is difficult in 3D, while it is simpler in 2D. For instance, facial animation has a well-developed set of styles in the realm of 2D cartooning, which are difficult to translate to a three dimensional model. With 2.5D cartoons, there approach can be used naturally and simply because of an animator's desired appearance for a cartoon object in a given frame can be drawn in directly without having to consider what 3D shape would produce the same effect.

However, 2.5D models have some limitations. It has no explicit 3D polygonal mesh of the object and characters. And it cannot be modeled directly with 3D mesh-based methods. Their operation do not support to show interior contour, shape silhouettes and detail lines at some plot in rotation. And their models do not support sharp and highly concave shapes of cartoon object, which cause interpolate poorly and overlapping strokes at some interior views. Some of this problems can be figured out by dividing the shape into some convex shapes, and then using UI tool Boolean union operations to group them into one. Hair is a difficult case to interpolate, which generally falls over the head in a way that forms a concave shell.

In conclusion, this is an extremely informative paper that clearly described the approach on 2.5D cartoon object and characters. It is a simple way to generate plausible rendering of the figures in new views.

Paper review: Semi-Supervised Co-Analysis of 3D Shape Styles from Projected Lines

This article present a semi-supervised co-analysis method for learning 3D shape styles from projected lines. An experiment was set within a collection of 3D shapes different from multiple categories and styles. And Analysis the result of projected feature lines of the 3D shapes. Multi-view feature integration and style clustering are carried out under the framework of partially shared latent factor (PSLF) learning, a multi-view feature learning scheme. PSLF learning is done by distilling and exploiting consistent and complementary feature information from multiple views, and it can be applied on multi-view fusion. The result of the analysis supports both unsupervised and semi-supervised analysis. However, we are focus on the semi-supervised model in this paper.

In computer graphic filed, styles are generally regarded as distinctive and recognizable forms. It follows that stylistic forms that serve to characterize a common style tend to share strong similarities, while between different style categories, these forms often exhibit clear distinctions. Especially for 2D and 3D shapes, styles can provide present all typical shapes people want. Most recent attempts have been on supervised learning of style similarity (Garces et al. 2014; Liu et al. 2015a; Lun et al. 2015) via crowdsourcing to collect user-specified style rankings and then performing metric learning rather than style clustering. Semi-supervised learning is attractive as it can take advantage of strong techniques for unsupervised clustering and discriminative analyses without the need to collect large amounts of user data. Also, we can find with semi-supervised learning, the human is not out of the loop. The learning process naturally incorporates user feedback to reflect the subjective nature of style perception, while keeping such feedback to a minimum. This method simultaneously achieves style clustering and style patch localization, which only weak supervision over a heterogeneous collection of 3D shapes spanning multiple object categories and multiple styles. The analysis also focuses on element level styles of 3D shapes which are decorative in nature. Such styles include those that are perceivable as patterns along shape contours or over shape surfaces, which are ubiquitous in man-made shapes. For some latent features those are sufficient for style comparisons, to spatially locate shape styles, one must eventually extract and discriminate between spatially explicit or visually apparent shape features. Analyzing these features for style is also well-motivated by the visual and perceptual nature of style recognition by humans: styles are seen as visual patterns. There is a concern on the projected feature lines do not exist in the "real world". However, they are believed to possess deep similarities to other more detailed and explicit visual representations as well as real scenes they depict. It is worth emphasizing that the feature lines are detected in 3D object space based on geometry analysis. Moreover, they tend to be more reliable than lines extracted from rendered images, which could be influenced by illumination and viewing artifacts. The semi-supervised method works more robustly with different 3D geometry representations and various shape imperfections including noise, incompleteness of shapes, and non-manifold geometries.

In condition of a heterogeneous collection of 3D shapes spanning multiple object categories and styles, our method performs style co-analysis over projected feature lines from each 3D shape and back project the learned style features onto the 3D shapes at the end. Furthermore, partially shared latent factor learning (PSLF) discovers shape styles by clustering shapes and selecting the most discriminative mid-level patches, which accentuate the clustering; this is consistent with how styles are typically characterized. This makes our PSLF-based feature learning and encoding more interpretable, especially in the context of view-based 3D shape style analysis, differentiating it from widely adopted end-to-end deep learning methods. The semi-supervised analysis takes the same types of user input as classical metric learning.

After reading this article, we can find the author demonstrate the effectiveness of our method for style analysis and patch localization, in particular, clear improvements over state-of-the-art supervised methods. Moreover, they also develop several applications which can take advantage of the detected styles.

There are still some field need to be improved in this method. For example, it can only extract stylistic elements that are visually apparent as feature lines and localized to the patch level. These do not include stylistic arrangements of patterns such as those involving symmetries and repetitions. Technically, the final style patch extraction hinges on the initial pre-selection of representative feature patches. And this creative method may lead to undesirable constrained clustering results.

Above all two article, one is about 2.5D cartoon and one is about an improvement method of 3D shape. We can find the improvement technology in the computer graphic, which can make both different kinds of virtual model become realistic in the computer world. However, as we can see in both paper, there still many limitations in each filed and drawback in the current state-of –art technique. So, in the future world, there are still more improvement need us to realize.