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Blending of three-dimensional geometric model shapes

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ABSTRACT

Three-dimensional (3D) geometric model shapes blending method can create various in-between models from two inputs of models shapes. Though, many blended shapes are implausible due to different inputs of model type, inappropriate matching-parts, improper parts-segmentation, and non-tally number of segmentation parts. are crucial and should be taken into account. The objective of this paper is to study the strengths and weaknesses of some prominent shapes blending methods and the 3D reconstruction methods. An interpolated shape blending program using the Laplacian-based contraction and Slinky-based segmentation method is developed to illustrate the critical problems arise in the shape blending process. Output results are to be compared with some prominent existing methods and one will observe the potential research direction in the blending research work.

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1. INTRODUCTION

Three-dimensional (3D) modeling is getting more and more important nowadays especially in the games and movies industries to meet the audiences' visual excitement. The most common modeling method is through using modeling software. The frequently used window-based modeling software are 3D Blender, Wings 3D, Meshmixer, FreeCAD, 3D Slash, and Sculptris. These open-source software however, are more suitable for the beginners, except 3D Blender which can create more advance stuff. Other advance but not free modeling software are 3D Maya, Houdini 17.5, Cinema 4D R20, Autodesk 3ds Max, and Lightwave 3D. They are more suitable for creating advance and complex graphic models and special effects. The software employ modeling techniques like spline/non-uniform rational B-spline (NURBS) modeling, subdivision/box modeling, contour modeling, digital sculpting and surface modeling [1], to speedily construct high quality of 3D models. In general, using the software to create 3D models still requires time, experiences and skills.

Another modeling technique is the image-based modeling which input two-dimensional (2D) or Two-and-a-half-dimensional (2.5D) static images to construct a 3D model. The more input of images, the more refined detail of the model would be generated. However, the processing time to construct the geometric details from the images and the combination of the piecewise detail from each image is undoubtedly will be increasing. This has not covered the processing time for calibrating the image sequences for the purpose of denoising and improving the quality of the image. Nevertheless, the latest research work is heading towards the un-calibrated work [2] and the minimal use of number of images to speed up the construction of the 3D models. Constructing a 3D model from the scratch is a pain [3] to many modelers in games and entertainment industries. It is an agony to come up with a new model design for the fresh visual excitement. One of the solutions to this problem is by using the model blending method. It blends (or combines) two or more input of 3D models and outputs a new design of 3D model automatically.

Next section, we will review some prominent blending methods. In section 3, we will discuss some 3D reconstruction techniques. Although processing the images is time-taking, this research area is getting more attention because if the number of images to be used reduces, it can shorten the processing time very much. In section 4, we will demonstrate a simple blending work and some results for visual understanding. Section 5 will discuss the future direction of the blending research work.

2. 3D BLENDING METHODS

Model shape blending and model shape morphing are two frequently overlapped terminologies used in many literatures. Technically, shape blending combines two or more model shapes to form a new shape. The new shape is expected to be the intermediate shape of all the inputs. For instance, in Figure 1, the long, slim and straight magenta object (left) is blended with a short, curvature cyan object (middle). This produces an average height, slight-curvature blue object (right).

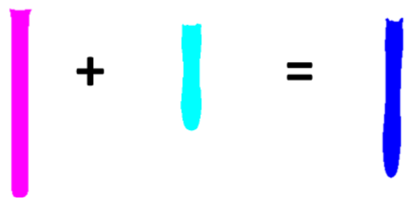


Figure 1. Two model shapes are blended to form a new shape

Meanwhile, shape morphing is a transition of shapes from one source of model to a targeted model. The result will be a sequential of models. The midway transited model may be similar to the blended model shape. Though, this method can only transact two model shapes at one moment. Unlike shape blending method, it not only can combine more than two model shapes at one moment, the resultant shape may completely be different from the input shapes. Therefore, shape blending method is more preferred for creating new ideas in the design world; whereas shape morphing is more preferred for creating animation in the interactive world. In this section, we will review and analyze on a few remarkable shape blending methods.

Jain *et al*. [4] analyzed each feature shape, its adjacency features and the symmetry features before combining parts to form an object. Their system performed hierarchical pairing between the shapes, combining parts which have almost the same positional information in the nodes of the hierarchy. The pairing is interpolated from coarse-to-fine parts and subsequently swaps and combines to produce new models. Their method does not involve any manual intervention. Though, the output is very much depended on the accuracy of the segmentation of the parts. Besides that, their algorithm needs to have equal matching parts. If one input has very little parts and the other input has a lot of parts, then, the final output will result to very little exchange of parts or might produce unpleasant models.

Alhashim *et al*. [5] and Wu *et al*. [6] applied structural-based concept to blend two topology-varying input model shapes. Their blended result comprised of the basic structure (or functional) of the input models. When blending two input chairs, the output should remain to be a chair-like model. To achieve that, they shrank the input models into a skeletal representation. Then, each skeletal part was identified and made corresponded between the source and target models semi-automatically (user input was involved). Blending process was executed via topological events in different orders. The preserved structure would filter off implausible in-between graph. The remaining unfiltered in-between structural graphs are mesh-reconstructed through an inverse mapping from the skeletal representation to the surfaces model. The method still requires a few improvements such as accurate segmentation for meaningful parts, proper parts corresponding for creating a logical functional shape, and the input model shapes are limited to tubular and sheet-like parts (non-complex shapes).

Huang *et al*. [7] interestingly blended two models to produce new stylized models. They inputted a base model which was purely a non-textured 3D geometric model, and a style model which was a textured 3D geometric model. The base model would dominate the basic shape of the new model. For instance, input a “stylized” cow model and a “base” cup model will result to a cow-like cup of shape. For blending the two inputs, Huang et al. constructed a tree-growing data structure to filter off the implausible parts-combined models based on six different aspects. Then, based on the topology merging graphs, they applied soft matching to combine the corresponding parts. Their proposed method can blend any models from different categories such as to blend a life object with a lifeless object, which is very different from previous works. Nevertheless, their method is complex and involves human intervention.

Ong *et al*. [8] applied slinky-based segmentation method to auto-segment input models into functional parts. Both models' parts were scaled, oriented and matched accordingly. Then, swapping of parts was executed to from one model to another model. Their method is simple but both models need to be equaled in number of parts. Also, their input models can only deal with the same object.

Hua *et al*. [9] employed Hausdorff distance method to match parts from two input models. They proposed two approaches to blend the matched parts. The first approach simply interpolates the vertices and faces from one part to the corresponding part for creating in-between parts. The second approach parameterized the part-pair spherically to a combined mesh and interpolate the vertex in the combined mesh for in-between parts. The created variations of models are of the plausible shape and with fine functionality. Though, the approaches require same category of objects for the blending such as to blend a round table with a square table, and both input models must share the same number of segmented parts.

3. 3D RECONSTRUCTION

3D reconstruction can be heavily device dependent or alternatively, a less costly approach which rely more on economic data acquisition and data processing techniques. The former approach usually requires investment on expensive devices or sensors to achieve high accuracy while latter approach invites opportunities for improvements in processing algorithms to obtain acceptable results. Research can range from investigating affordable setups and instrument for data acquisition to designing frameworks to filter/manage/process data and reconstruct 3D surface. The discussion in this section will be categorized to modelling objects, human face and body/pose, and environment like room, terrain or building.

3.1. Modeling objects

With the rapid advancements in camera technology and computer processors, image-based modeling (IBM) is gaining momentum. Rather than investing on costly devices like coordinate measuring machines (CMM) or laser scanners to achieve high accuracy, researchers invest their effort in investigating approaches to perform 3D reconstruction using more affordable and easily available hardware like consumer digital cameras, webcams or even build in cameras on mobile phones. Shujaa and Abdulmajeed [10] applied neural network (NN) technique for the depth estimation process.

Some researchers use red, green and blue color (RGB-D) sensors like Microsoft Kinect for 3D reconstructions, where Kinect v1 and v2 each uses structured light (SL) and time of flight (ToF). The former deducts the distance based on the infrared (IR) pattern's distortion on the object's surface while the latter captures the time used for light to travel to the object surface and reflected to the receiver. Kinect v1 is suitable for indoors only as it does not perform well under bright sunlight [11] and the accuracy decreases exponentially with increasing distance [12]. Yang *et al*. [13], Kinect has few advantages, including the ability to perform well under low light conditions, to resolve pose silhouette ambiguities, and is color and texture invariant.

According to Durou *et al*. [14], 3D reconstruction techniques from digital cameras can be classified as either geometric or photometric and the number of images required is either single or multiple, as show in Table 1. Geometric shape-from-X techniques identify features from the images, while photometric shape-from-X techniques analyze the quantity of light received in each photosite of the camera's sensor.

Table 1. Main shape-from-X techniques [14]

	Geometric techniques	Photometric techniques
Single image	Structured light Shape-from-shadows Shape-from-contours Shape-from-texture Shape-from-template	Shape-from-shading (SfS)
Multi-images	Structure-from-motion Stereopsis Shape-from-silhouettes Shape-from-focus	Photometric stereo Shape-from-polarisation (SfP)

Boora *et al*. [2] attempted to perform 3D reconstruction with images obtained from mobile phones. Tracking was done with Kanade-Lucas-Tomasi (KLT) feature tracking algorithmand then the feature points were projected to approximate the 3D world point. Nevertheless, the authors were unable to obtain the actual size of object. On the other hand, Ng [15] performed depth value approximation with Lucas Kanade optical flow and trigonometry. Images of 640x480 pixels were taken using webcam and the actual size of objects were able to be approximated in a calibrated environment.

Yamada and Kimura [16] evaluated the performance of two famous keypoint detection/feature descriptor used for 3D reconstruction, namely scale invariant feature transform (SIFT) [17] and accelerated-KAZE (AKAZE) [18]. They found that AKAZE performed slightly better than SIFT, but sufficient 3D reconstruction were not obtained if only the descriptors were used separately, and hence, they proposed the combination of both to obtain better 3D reconstruction results.

Most of the times, when performing IBM, problems like hole or noise will occur. Holes might be due to lack of features to track, or part(s) of the subject was occluded. Awang *et al*. [19] proposed enhanced advancing front mesh (EAFM) method to overcome the problem of finding new point in a hole of missing area. The enhanced method was an improvement of the original advanced front method (AFM) and their results was able to introduce more points in a hole to represent better features of the object. On the other hand, problem will occur in active systems like laser scanner when trying to obtain 3D points of surfaces which do not reflect light, such as black or transparent surfaces.

3.2. Modeling human

Human face modeling with Microsoft Kinect has also lots of room for research, especially after the release of Kinect v2 in 2014. Wasenmüller and Stricker [12] have evaluated that Kinect v2 outperformed Kinect v1 in terms of usage in 3D reconstruction, simultaneous localization and mapping (SLAM) or visual odometry. Human reconstruction using Kinect basically can be either focusing on the face only [20], or on the body/pose [21]. According to Zheng *et al*. [22], research findings in image-based reconstruction of a human body can be useful for virtual reality (VR) and augmented reality (AR) content creation. They proposed a deep-learning based framework to reconstruct 3D human model using a single image.

3.3. Modeling environment

When talking about indoor reconstructions, 3D room can be obtained either using Microsoft Kinect [23]-[25] or image [26]. To overcome the problem of visual attributes’ limitations such as transparent and highly reflective objects such as windows or mirrors, Kim *et al*. [27] proposed the combined usage of audio-visual data to complement the visual limitations. They captured the environment with 360∘ cameras and recorded acoustic room impulse responses (RIRs) with a loudspeaker and compact microphone array. Depth information of the scene is recovered by stereo matching from the captured images and estimation of major acoustic reflector locations from the sound.

Meanwhile, for modeling large outdoor areas such as buildings or terrains, light detection and ranging (LiDAR) will be used. Its instrument fires up to 150,000 pulses per second of laser light at a surface. Like ToF cameras, the distance is deducted by the amount of time it takes for each pulse to bounce back to the instrument. Generally, LiDAR can be categorized into airborne LiDAR and ground-based LiDAR. Airborne LiDAR can provide higher levels of detail and hence is a more popular source of terrain mapping [28]. Their usages include forestry management and planning, oil and gas exploration, archaeology and many more. Meanwhile, ground-based LiDAR is used for more localized reconstructions, such as building reconstruction and navigation for autonomous vehicles. Yang and Fan [29] used 3D LiDAR points to reconstruct buildings. The filtered data is processed using random sample consensus (RANSAC) algorithm and region-growing algorithm for plane detection. Finally, the authors reconstruct the 3D building using the four corner points of the plane. On the other hand, Ashraf *et al*. [30] implemented synthetic aperture radar (SAR) for reconstruction by processing of radar echoes based on adaptive orthogonal matching pursuit (OMP) compression sensing.

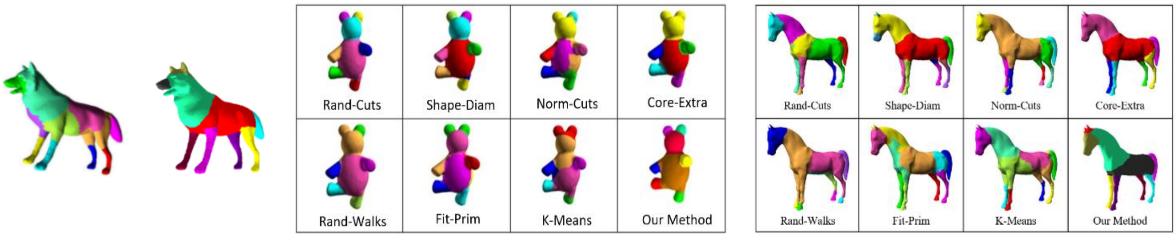
On the other hand, building and terrain modeling can also be performed using ariel images. Ban *et al*. [31] utilize height map generated from a satellite image and then perform refinement of 3D mesh to remove stair shape on the side of buildings. Meanwhile, Sugiura *et al*. [32] proposed high quality 3D surface reconstruction, specially for man-made structures, as triangular meshes by combining 3D line segments with the point cloud obtained from Structure from motion (SfM).

4. ANALYSIS ON THE POTENTIAL RESEARCH PROBLEMS IN 3D BLENDING WORK

This section will discuss the potential problems while working on the 3D blending research work. The examples given in this section are our implemented interpolation of geometric model blending using the Laplacian-based contraction and Slinky-based segmentation method [33]-[34]. Due to limited paper length, readers may refer to the cited papers for more information on the contraction and segmentation methods. The following will focus only on the blended-related output results.

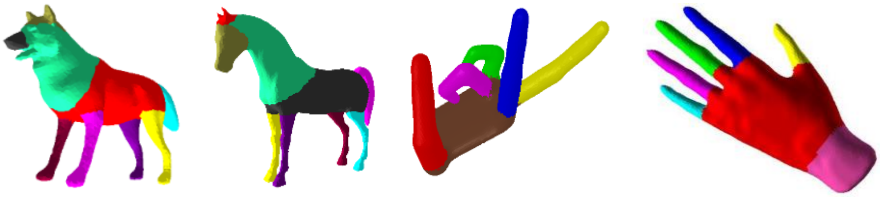
Most of the blending techniques require input objects to be accurately segmented for functional parts [35]-[36], so that their appearance is plausible and meaningful for latter blending activity. Figure 2 exhibits the quality of the model segmentation. Figure 2(a) shows two dogs, which the (left) dog is poorly segmented and the (right) dog is appropriately segmented. The poor segmented model will lead to many implausible parts. The over-segmented parts will result to open mesh which will create a lot of unwanted holes. Figure 2(b) shows the comparison of our proposed method to the existing seven prominent methods. The details of the seven methods are discussed in [33]. Accurate segmentation plays a very crucial role to ensure the correctness at the preliminary stage. Otherwise, the following processes and output results will all be deviated.

Part-matching is another crucial criterion to take into account. Many existing blending methods (except the method proposed by Huang *et al*. [7]) require the input models to be the similar type and same number of segmented parts. Figure 3 exhibits the input model type. Figure 3(a) shows the same type and same number of segmented parts. If both the models do not share the same number of segmented parts (e.g. Figure 3(b)), then, the model with more parts shall merge some of the parts. This stage will require some intelligences to choose the most suitable parts to merge. For Figure 3(b) right hand model, the best choice is merging the palm with the wrist, and not merging the palm with any finger. This can be determined via skeleton analysis which is not within the scope of our discussion here.



(a) (b)

Figure 2. Quality of the model segmentation (a) poor-segmented left-dog model and well-segmented right-dog model and (b) comparison between our proposed method with seven existing prominent methods



(a) (b)

Figure 3. Input model type (a) both input models are of same type and same number of segmented parts and (b) both models are of same type but with different number of segmented parts

Part-blending process or part-swapping process does not usually produce obvious weird result. They are simply interpolated (or exchange) from one source part to the targeted part. Figure 4 exhibits the blended result. Figure 4(a) shows two legs of the chairs are blended. The source leg is thick and slanted; the target leg is slim and straight. The blended leg is less thick and is slightly slanted. The result is plausible, but a straighter leg is preferred for the stability purpose. Figure 4(b) shows a blended oval/diamond from a cuboid and a sphere/diamond. Technically, the orientation of the target part should be preserved. Only the size or the shape of the part is modifiable.

The last critical activity of the blending process is to ensure the blended part attach properly or realistically to the original model. In Figure 5, it shows that the blended leg is not properly attached to the seat of a chair. Though, this is not a difficult problem. One can simply find the centric coordinates of the seat-hole and the blended-leg-hole, and then translate and orientate the blended-leg hole to merge with the Seat-hole.

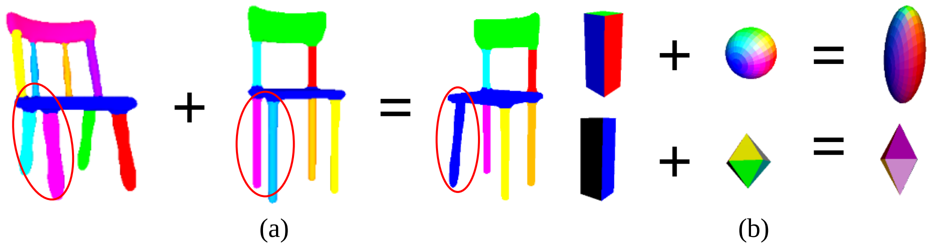


Figure 4. Blended result (a) source part (left), target part (middle), blended leg (right) and (b) source part (left), target part (middle), blended oval/diamond (right)

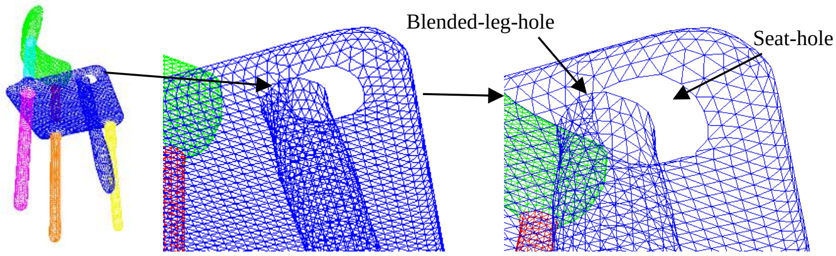


Figure 5. Blended leg is not properly attached to the model (bottom view)

5. FUTURE DIRECTION OF 3D BLENDING

Many proposed blending methods are either semi-automatic or involve some human intervention to pair the functional parts. This has not included the human intervention in segmenting the models. At present, computer is still unable to imitate human brain to determine the orientation of various models, so that it can properly align and match the parts accurately. Many existing methods applied structured link among the segmented parts and tried blending the parts hoping to form a logical model. Deep learning approach is one of the potential areas for solving this problem. So far, not many deep learning approaches have been applied in three-dimensional field. This may deal to the already complicated neural network in two-dimensional field. The extension may exponentially burden the memory and the computation performance.

Blending method is gradually widely applied to many industrials such as manufacturing industry, civil construction industry, automobile industry, and entertainment industry. by blending existing products/models for different products/models design. The input models are no longer the simple model meshes and/or small object size, but could be more than billion points of coordinates and/or huge and complex 3D screen. The used of graphics processing unit (GPU) may be insufficient to handle its bottleneck.

6. CONCLUSION

This paper reviews a few prominent 3D blending methods and 3D reconstruction methods for creating new or in-between models. It has also discussed some potential blending problems to solve at present time and some future direction of the model blending activities in the industries. A blending program is developed to illustrate the results and the potential problems. The 3D segmented result is to be compared with some existing prominent methods. Some blended results are demonstrated using the primitive models.

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