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Mapping Bootstrap Error for Bilateral Smoothing on Point Set

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Abstract. In this study, point set smoothing on surface reconstruction is developed. In surface reconstruction, the objective is to find the best surface representations of a modeled object. Surface representations of 3D model are created from 3D point sets. The raw data from optical devices such as laser scanner always contain noise. The surface reconstruction process should yield consideration to this data noise for a better representation of the modeled object. Surface reconstruction from sample points is a difficult challenge and the problem arise in application such as medical imaging, visualization and reverse engineering. Bootstrap is a model averaging technique and widely used in applications such as noise estimation. We used the implementation of bootstrap error estimates on point sets to perform smoothing on noisy models. Given a noisy model of a point cloud, error is estimated on each point using bootstrap error estimation. Then, a surface representation is reconstructed from the set of point clouds. We model a function or algorithm that could adapt the density of the model based on bootstrap error estimation to avoid oversmoothing, irregular noise on the data and feature preservation. To smooth the model, we use the concept of bilateral filtering found in noise filtering of 2D image. We compare the curve fitting in linear mapping and quadratic mapping in which the quadratic mappings have two models. In this paper, we used bootstrap error estimates to guide a projection based on point set smoothing algorithm. As a result, the noisy points were smooth out and our model had been recovered. We expect that bilateral smoothing would avoid over smoothing the feature areas and feature of the model preserved.

Keywords: Surface reconstruction, point set, bootstrap, bilateral smoothing.
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INTRODUCTION

Surface reconstruction is about finding the best surface representations of a modeled object. The data is usually obtained from a 3D scanner in the form of point clouds. Few issues that may arise are the noisy points, feature preservations and smoothness of the model. Typically, researchers in this field handle the issues arised in surface reconstruction separately. In our research, we concentrate on the postprocessing part of surface reconstruction which is smoothing.

To perform smoothing on noisy models, we used the implementation of bootstrap error estimates on point sets. The bootstrap was introduced by [1] as a computer based method to estimate the standard deviation. Bootstrap error estimation is an averaging statistical method to predict the error value or other statistical values of a fitting. An advantage of the bootstrap is that it allows us to compute maximum likelihood estimates of standard errors and other quantities when no closed form solutions are available. An equation is said to be a closed form solution if it solves a given problem in terms of functions and mathematical operations from a given generally accepted set [2]. For example, an infinite sum would not generally be considered closed-form. However, the choice of what to call closed-form and what not is rather arbitrary since a new "closed-form" function could simply be defined in terms of the infinite sum. We use polynomial surfaces for our fitting and error value to recover the data. Given a noisy model of a point cloud, error is estimated on each point using bootstrap error estimation [3]. We may also apply other preprocessing step such as outlier removal, simplification or denoising when we obtain the point clouds. Then, a surface representation is reconstructed from the set of point clouds.

In particular, the issue is to reconstruct a surface from point clouds. We model a function or algorithm that could deal or adapt to the existing issue such as the density of the model to avoid oversmoothing, the irregular noise on the data and feature preservation. We can use the test error estimates to identify bad quality fittings and avoid using them for denoising. Postprocessing steps may include some more denoising or smoothing if the data was still noisy. We want to make sure that the feature is well preserved if the model contains sharp edges. Some experimental results demonstrate that the algorithm is robust and can smooth out the noise efficiently while preserving the surface features.

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We followed our work in [4] to produce the Bilateral Filtering part. In this paper, we demonstrate the difference mapping for our bootstrap estimates. We tested two cases of quadratic mapping and compared the result.

Bilateral Filtering

Bilateral can be defined as having identical parts on each side of an axis while in image processing and computer vision, filtering is a removal of something unwanted. Generally, bilateral filtering is a simple, non-iterative scheme for edge-preserving smoothing. Bilateral smoothing is a non-linear filtering technique introduced by [5]. Before the Laplacian edge detection, we apply bilateral filtering to our original model to smooth out the noise and maintaining the edges. It was able to enhance the edges without amplifying the noise.

Furthermore, we wish to undertake all points in the neighborhood with polynomial fitting that we used in the bootstrapping step. We use the bootstrap surfaces to denoise the point set in an application of the bootstrap method for test error estimation. In that case, we can detect the poor quality fittings and avoid denoising. In particular, each point is projected to the average of the values at that point of all the bootstrap models, that is

$$(x_i, y_i) \rightarrow \left(x_i, \sum_{b=1}^{B} f^{*b}(x_i) \right)$$

The bilateral filter takes a weighted sum in a local neighborhood where the weights depend on both the spatial distance and the intensity distance. While noise is averaged out, the edges are preserved well from this way. Based on locally fitted surfaces, noise may increase due to low quality surface fitting. In that case, while avoiding surface degradation near the features, the proposed algorithm can remove the noise as we assume that the main source of test error is surface features rather than noise.

Given the point set of $Z = \{z_1, z_2, z_3, \ldots, z_N\}$, bootstrap samples are produced from a random sampling of Z. We run the bootstrapping of the polynomial fitting for each point z_i on its *K*- neighborhood to obtain the estimated projection $z_{i,j}^B$ and its error W_i. We fit the bootstrap samples to a function and repeat the process for B times.

Let $\{z_{i,1}, z_{i,2}, z_{i,3}, \ldots z_{i,K}\}$ be the neighborhood of *K* nearest points around the considered points $z_{i,0}$. Following [4], we would project each point of the neighborhood given by

$$z_{i,j \rightarrow (1-w_{i,j})} z_{i,j} + w_{i,j} z_{i,j}^B$$

and the weight is given by

$$w_{i,j} = \theta_1 \left(\left\| z_{i,j} - z_{i,0} \right\| \right) \theta_2 (W_i)$$

The function $\theta_k(x) = G(x, h_k)$ is a weight function with $k = 1,2$ and standard deviation is denoted as h_k with zero mean. The Gaussian function defined as

$$G(x, h_k) = e^{-x^2 / h_k^2}$$

The standard deviation h_k are user-defined parameters value according to its θ_k that will influence our results. Although the bootstrap projection has improved the noisy model to make it smoother than before, a bilateral filtering provides a neighborhood individually and its error estimation improves the quality of the fitting.

Results

The validation of test error estimations in the context of surface reconstruction from noisy point sets is a challenging task. It is difficult to obtain reliable independent estimates of the test error for comparison. We can see the error estimation on different value of *K*-nearest neighborhood for our verification. This is smoothing algorithms which rely on factors from distance and error value from neighboring points.

Figure 2 shows the result of the Bunny model with 0.3, 0.5, 0.7 and 1.0 noise level after being smoothed with the bilateral filters for different values of h_1 and h_2 after 300 iterations. Figure 1 and Figure 3 show results with different h_2.

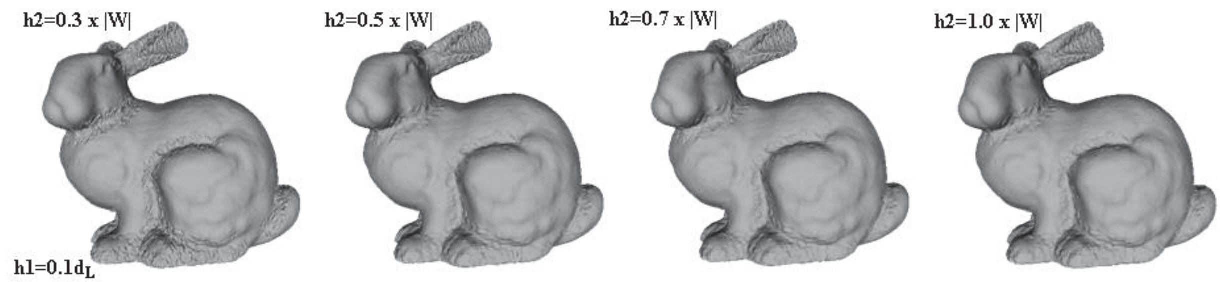

FIGURE 1. The effect of bilateral smoothing for different values of h_2 on the Bunny in linear mapping.

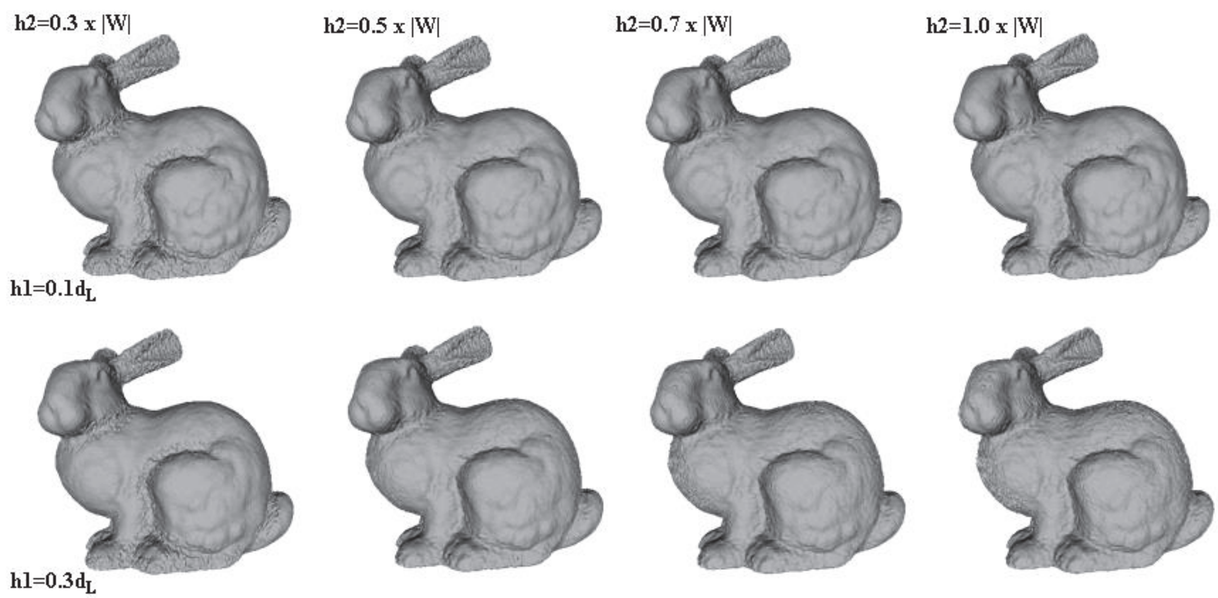

FIGURE 2. The effect of bilateral smoothing for different values of h_1 and h_2 on the Bunny in Model quadratic mapping.

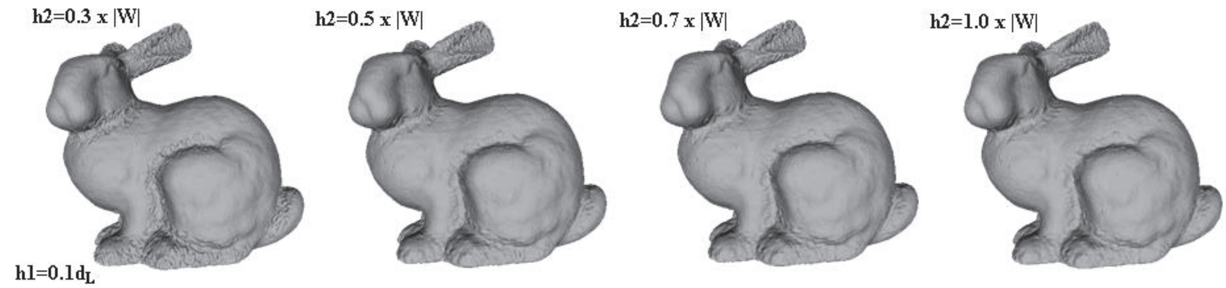

FIGURE 3. The effect of bilateral smoothing for different values of h_2 on the Bunny in Model II quadratic mapping.

Figure 1 is the model result from the positive linear mapping [4] as shown in figure below.

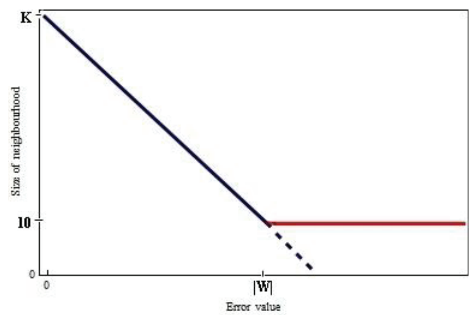

FIGURE 4. Heuristic neighbourhood selection by positive linear mapping in different value error.

Figure 4 shows that the linear mapping. We use the linear equation

$$f(x) = \left(\frac{10-K}{|W|}\right)x + K$$

where K is the size of neighbourhood of the data of the model and $|W|$ an average of the error values. In this case, we use 200 neighbourhoods. As the point arrived at $\{|X|,10\}$, the line become constant. So, at this point, the gradient of *f(x)* is equal to zero.

Besides, we have applied the same algorithm on $h_1 = 0.3d_L$ for bunny within linear mapping. We found that the model has been overprojected. By increasing the value of h_1, the featured area is oversmoothed and the other area would be overprojected. Consider Bunny in Figure 1, the feature area which is around its ears causes higher value of error. In this case, this is the result of a bad fitting, due to the fact that polynomial fitting that we have used in that particular area does not estimate well.

The bilateral smoothing with different h_2 values is also shown. We could see that the use of different h_2 gives different degrees of smoothness. As shown in Figure 1, the model is still noisy when h_2 is valued at half of the model error. Increasing h_2 to 0.7 and 1.0 of the model error would give us a better smoothing.

Figure 2 is the model result from the positive Model I quadratic mapping as shown in figure 5 below.

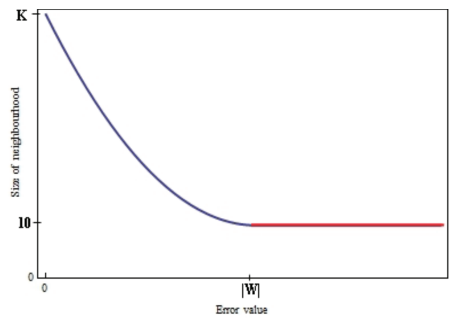

FIGURE 5. Heuristic neighbourhood selection by positive Model I quadratic mapping in different value error.

Figure 5 shows the positive quadratic mapping mapping. We use the quadratic equation

$$f(x)=\left(\frac{K-10}{|W|^2}\right)x^2+\left(\frac{(-2k+20)}{|W|}\right)x+K$$

where *K* is the size of neighbourhood which is user-defined and |*W*| an average of the error values in which it is the expected value of w_i . In this case, we also use 200 neighbourhoods. As the point arrived at $\{|X|,10\}$, the line become constant. So, at this point, the gradient of *f(x)* is equal to zero.

We have also run the same algorithm on $h_1 = 0.3d_L$ for bunny within Model I quadratic mapping. We found that the model is less overprojected compared to bunny with positive linear mapping. We can see that the feature areas of the bunny, such as the ears, hair and the edges at the bottom of the bust, are badly smoothed in Figure 2. The feature area is oversmoothed and the other area would be overprojected as we increase the value of h_1 .

The bilateral smoothing with different h_2 values is also shown in Figure 2. We could see that the use of different h_2 gives different degrees of smoothness. The model becomes smooth and the feature area is better preserved as we increase h_2 to 0.7 and 1.0 of the model error or to the full value of model error. As we can see in Figure 1.2, for $h_1 = 0.1d_L$, the leg and body of the bunny starts to deform and feature area is preserved when the h_2 value increases, that is, the weight of the bootstrap error parameter diminishes. While, for $h_1 = 0.3d_L$, the leg of the Bunny starts to deform when the h_2 value increases but the body area is a bit overprojected because the body area is rough.

Figure 3 is the result from the positive Model II quadratic mapping as shown in figure 6 below.

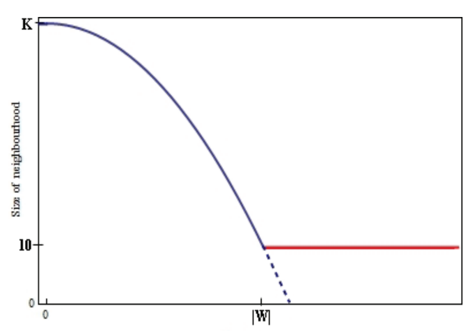

FIGURE 6. Heuristic neighbourhood selection by positive Model II quadratic mapping in different value error.

Figure 6 shows the negative quadratic mapping mapping in different value error. We use the quadratic equation

$$f(x) = \left(\frac{K-10}{|W|^2} \right) x^2 + K$$

Where K is the size of neighbourhood which is user-defined and $|W|$ an average of the error values in which it is the expected value of w_i. Same like the cases before, we use 200 neighbourhoods.As the point arrived at $\{|X|,10\}$, the line become constant. So, at this point, the gradient of *f(x)* is equal to zero with x is 0.

In particular, we have also run the same algorithm on $h_1 = 0.3d_L$ for Bunny within Model II quadratic mapping. We found that the model is overprojected compared to Bunny within Model I quadratic mapping.

The bilateral smoothing with different h_2 values is also shown in Figure 3. We could see that the use of different h_2 gives different degrees of smoothness. The model becomes smooth and the feature area is better preserved slightly compared to Bunny in Figure 2. As we increase h_2 to 0.7 and 1.0 of the model error, we get better smoothing.

Overall, Bunny model projected with Model I quadratic mapping produce better smoothing and better feature preservation compared to both linear mapping and Model II quadratic mapping. It can be observed that Bunny in Model I quadratic mapping is not oversmoothed and overprojected when we increase the h_1 value. Increasing h_2 values preserve and smooth the feature nicely. While the feature of eyes and mouth is preserved, the area around the leg is also smooth.

CONCLUSION

We have presented an error mapping for bootstrap error in the context of surface reconstruction. The primary purpose of this study is to investigate the improved smoothing using quadratic mapping. In our case, we used error values as one of the weights. While the method can smooth the model, one of the issues worth analyzing is to find the value for the variances h_1 and h_2 automatically. Another limitation is that this method may not be able to preserve sharp edges. This is a common limitation of point smoothing based on averaging of neighboring points.

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