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Morphological Improvements for Photogrammetry-based 3D Reconstruction of Historic Monuments

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ABSTRACT

Reconstruction of 3D surfaces for restoration and digital preservation of geospatial structures has vital applications. Photogrammetry-based reconstruction is one way to produce near-optimal results but suffers from surface quality issues especially when working with inadequate or missing image frames. This effectively results in reduced quality of the generated surface. This paper suggests improving photogrammetry-based 3D surface generation by incorporating filtering and extrapolating control vertices for approximating the surface. For this purpose, methods like moving average filter, local regression, and exponential smoothing methods have been studied for surface approximation. The improvement in the quality of the generated surface is visually and structurally verified by triangulating and rendering. The proposed framework enables to overcome of small holes and generate an optimized approximation of the surface. The paper also studies the improvement in surface quality by applying them to the tone-adjusted set of images. The proposed reconstruction method has been applied to the data acquired for a historic fort situated at Ahmednagar in Maharashtra, India. The results of the experimental work advocate the use of color tone adjustments, smoothing, and interpolation of points in 3D space as an integrated framework for improved 3D reconstruction and visualization of historic monuments. The reconstructed 3D surface exhibits a higher degree of resemblance to that of the actual and theoretical physical structure of the monument.

Keywords: *3D Reconstruction, Digital Restoration, Surface Smoothing, Photogrammetry, Building Modeling*

1. INTRODUCTION

3D surface data such as point clouds are now finding more diversified applications than before due to the availability of improved hardware, advanced algorithms and, software tool than ever before. A *point cloud* is a collection of data points distributed in 3D space. These points approximate the shape and the surface of the 3D object. Point cloud has been an important format of input data for complex problems like surface reconstruction and visualization[1] of the geographical phenomenon, spatial features, and man-made building structures[2]. It finds interesting applications like digital surface reconstruction, digital restoration, and 3D visualization of old historical monuments. There is a shift towards 3D analysis and visualization of objects as they provide better opportunities to uncover missing information and provides improved visual experience. 2D visualization has limited use and has ceased to be used for large geospatial objects for practical reasons. While 3D visualization offers more benefits but it is highly dependent on data quality and the format of data.

Point cloud data can be made available using sensing equipment like LiDAR. While LiDAR-based data are more capable of 3D point approximation of the surface, but they may not be readily available for experimentation and visualization[3], [4] purpose besides the cost of acquiring them. One way to overcome this is to use the photogrammetry-based reconstruction[5] method and render them for visualization. Among several methods available for reconstruction, photogrammetry[6] tends to produce a near-optimal 3D reconstruction. It is based on deriving metric information for the given object by estimating the physical measurement of the structure under investigation from its photographs. Photogrammetry[7] is a multistage process of constructing a 3D approximation from a set of photographs. Many software[8] solutions are available today for photogrammetry-based reconstruction. Metadata(Photoscan) one of the software solutions that emerge as the leader among all. While the software achieved much of the expectations, it often needs improvements in input and intermediatory stages.

Restoration and 3D reconstruction of the building[9] especially historic monuments can use both LiDAR sensors data as well as 3D data generated from photogrammetry. The results are more accurate when high-resolution clear images are used with a centrally projected system adhering to object geometry and visual perspectives. This motivates using photogrammetry for the digital visualization of surface structures. It must be noted that due to physical conditions and accessibility constraints, there may be a limited set of images and restricted space; which often lead to deformed structure in the reconstructed surface. The use of inadequate and misaligned images results in poor and incomplete 3D reconstructions. The problem becomes more aggravated when photographs are sparse, they have taken from limited orientations and space coverage. One of the approaches to address such a problem is to extrapolate missing data in the images and perform local data smoothing approximations. These extrapolated and smoothened surface points help in better representation of the surface and can even predict lost surfaces to some extent. Another way to address the problem is to preprocess the input images by morphologically improving[10] color distributions

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within the image for better results. Thus tonal adjustment of pixel intensity can also lead to potential improvements in the generated 3D surface.

This paper attempts to study and apply smoothing operations on 3D points obtained from a set of test images during the photogrammetry process and finally generates an improved surface. The surface is generated by extrapolating images and rearranging control points for triangulating surfaces during reconstruction. It also compares these 3D results obtained from tonal adjustments [10] and highlights future pointers for 3D reconstruction and visualization.

2. RELATED WORK

Digital reconstruction of geospatial structures like buildings and historic monuments helps in more effective and immersive visualization. The problem of reconstruction has been studied in several ways. 3D reconstruction and visualization in [11] discuss the use of measurements of geo-referenced points for the restoration of historic buildings. The paper emphasized the use of Interpolation methods to obtain a detailed geometric mesh when few points are known on the surface. It also highlighted that computation of surface geometries requires creating the mesh from a set of existing points as vertices to approximate the surface.

The significance of LiDAR-based surface reconstruction has been studied in [12,13,14]. These studies explain the issues and effects of structural constraints and also compares airborne LiDAR with image matching techniques for surface reconstruction. This work shows that LiDAR generates a better surface approximation of 3D objects when precise surface returns are obtained densely covering the surface. However, it is observed that further consideration must be done for steep changes and samples for large vertical differences. Historical monuments often have large and steep structures that need additional attention. The use of point cloud data for reconstruction is also endorsed in [15] for its use in archeological models. Archeological structures need more care as they can be negatively affected if handled inappropriately. Hence methods of data acquisition from range sensors like LiDAR sensors and data derived from methods like photogrammetry are found useful. Photogrammetry-based reconstruction of the ancient monument in [16] demonstrates the ability to visualize geospatial structures with ease. It is observed that close-range photogrammetry and image correlation can be vital in retrieving the precise metric data on irregular surfaces. While photogrammetry is a well-established method, it still needs approximation in the region with sparse coverage and inadequate overlaps.

Some related work has been done previously for the generation of elevation models [17], increasing the fidelity of 3D models for photogrammetric mapping of cultural heritage materials [18], and model corrections by improving camera calibration [19]. These studies suggest that while laser scanning systems like LiDAR generate better surface geometry, photogrammetry is more useful for generating accurate textures. For recording and modeling medium and small artifacts, photogrammetric recordings [20] are preferred and confirm that photogrammetry surpassed the laser scanning method. An important application of photogrammetry-based reconstruction is the detection of damages[21] in a historic building and surface analysis. It highlights the nondestructive nature of surface reconstruction and visualization through photogrammetry. Primarily, such assessments can be easily done through 3D surface analysis using mathematical/morphological operation on point cloud data generated during photogrammetry-based reconstructions.

Every method has scope for improvement with the developments in hardware and software. The photogrammetric process generates a set of control points in the form of points cloud as an intermediate output. These data points correspond to the surface point of the geospatial object positioned in 3D space. As these points are generated from a set of images, smoothing these data points can help in removing noise and outliers and fill in the missing data points. One of the fundamental assumptions with photogrammetry-based reconstruction is that the data does not comprise of small-scale structure. Therefore, smoothing operations do not tend to deform the overall structure of the object. This property makes local and global operations on point cloud more feasible and thereby approximating the surface digitally. However missing points over a span would affect the quality of the generated surface.

The study shows that the 3D results obtained from photogrammetry-based methods can be further improved. This can be done especially by improving the input images and also by processing point clouds generated at the later stages. This will be useful in generating elevation models and modeling large landscapes and building structures. While there are several technologies and methods for 3D reconstruction[22], photogrammetry seems to be one of the good ways to do it. Several areas have been identified for improving the 3D reconstruction process. Some of these include slope surface displacement, improving tonal intensities of the input images, and optimizing point cloud generated by photogrammetry before generating the final triangulated and textured surface. This papers address and explore the usefulness of some of these to improve the quality of the generated surface.

3. IMPROVING PHOTOGRAMMETRY BASED RECONSTRUCTION

The environmental conditions during image acquisition greatly affect the data for photogrammetry. Proper exposure, lighting condition, and distance are important for aquiring data which will lead to better surface approximation through photogrammetry. While the use of a large number of images may be able to overcome the problem of approximation, color tones and intensity in the image have an impact on the final approximations. Improvement in the color tones[10] that includes adjustments in brightness and contrast values, can greatly help to improve the results. The empirical estimates for tonal adjustment can be computed and it can be integrated in the recnstriction steps just before features are extracted and a dense point cloud is generated for it. It can also be useful for surface generation solutions for outdoor structures including buildings and monuments.

A fundamental area where photogrammetry can be improved is handling missing or outlier data. The problem of missing data and outlier data can be resolved by smoothing operations. Data smoothing is widely seen as a statistical technique for eliminating outliers from the available data set, and sometimes we can extend it to estimate missing data values to create better approximations. Smoothing not only helps in the study of data characteristics but also can be used to comprehend geospatial data for approximating surfaces especially for 3D data samples defined in space. During the photogrammetric reconstruction of a given surface, we can estimate the surface point $S(x, y, z)$ from a set of control/dense points. This can even be done when the shape of the surface profile is unknown. Inherently, a group of geospatial data points in co-located space has spatial cohesion, and thus enables to compute the average or fit a parametric model to help in generating better surfaces. This aspect of smoothing operation on the given 3D data points organized as point cloud can be very useful in surface approximation, reconstruction, and hence also in 3D visualization.

Among several methods of smoothing point cloud data some widely used methods include moving average smoothing, local regression smoothing, random walk, spline-based smoothing, and exponential smoothing. Among these, we explore the use of moving average smoothing, local regression, and exponential smoothing methods on control points generated during the photogrammetry workflow to improve the regenerated surface.

Moving average smoothing-based filtering method updates each data point within a defined span with the average of its neighboring data points. The updated responses are obtained as

$$y_s(i,j) = \frac{1}{2N+1}\left[y(i+N,j) + y(i-N,j) + y(i,j-N) + y(i,j+N)\right] \quad \ldots(1)$$

where $y_s(i, j)$ corresponds to the smoothed value for the $(i, j)^{th}$ the data point, N denotes the number of neighboring data points considered for smoothing on either side of $y_s(i, j)$, and $2N + 1$ defines the span of the smoothing filter. One of the benefits of using this filter is that there is no constraint to have uniformly spaced data points. However, the span must be odd-ordered to maintain uniformity. The span can take values 1…N.

The *local regression* method of smoothing data is also sometimes referred to as local polynomial regression or moving regression. Local regression is effectively a generalization of moving average and polynomial regression[23]. In this method, the smoothed data value is computed using neighboring data points contained within the evaluating span. We rely on the weighted process for smoothing surface data by using a regression weight function for the data points confined within the span. Contrary to the moving average method, the order of the span used with the local regression-based computation can be either even or odd. The regression weight for data points in the model is defined as

$$w_{ij} = \left(1 - \left|\frac{z - z_{ij}}{d(z)}\right|^3\right) \quad \ldots(2)$$

where z is the depth value linked with the response value to be smoothed, z_i denotes the nearest neighbors of data point z defined by the span, and $d(z)$ denotes the distance along the abscissa from z to the most distant predictor value contained within the span being considered. The idea of using such a regression weight is to ensure that the data value which needs to be smoothed has maximum influence on the surface approximation. Any point outside the span area would have zero influence and hence zero weight value. During the data smoothing process, a first-degree polynomial is used to perform the weighted linear least squares regression. This is analogous to locally weighted scatterplot smoothing (LOWESS) of data values. Contrary to it, the locally estimated scatterplot smoothing (LOESS) method uses a second-degree polynomial to fit the data values. The resulting smoothed data value corresponds to the weighted regress obtained as the predictor value. If the neighboring points considered for smoothening a given data point are the same along with both directions then the weight function is said to be symmetric else asymmetric. The size of the span in this method is fixed and does not change like the moving average method. This has a different effect on the surface point approximation and the points for correspondence with each other.

The *exponential Smoothing* method is useful when short-range predictions are used. For large ranges or distances, the results may be relatively unreliable. This method is effective when data points have relatively slow spatial variation in space. To take into account the possibility of a trend in the generated point cloud, second-order exponential smoothing can be used. Note that the result is good when data follows a relatively linear trend. The smoothing formula is

$$s_t = \alpha p_i + (1 - \alpha)(s_{i-1} + b_{i-1})$$

$$\beta_i = \beta(s_i - s_{i-1}) + (1 - \beta)b_{i-1} \quad \ldots(3)$$

where s_i is the smoothing value at the current point p_i, α is called the smoothing factor of data($0 < \alpha < 1$), β is called the factor of trend smoothing ($0 < \beta < 1$) and b_t is the optimal estimate.

This paper attempts to exhibit the effect of morphologically improving and optimizing point cloud obtained during photogrammetry by applying methods discussed above to generate smooth approximations to the point cloud and thereafter compare their quality and performance.

4. EXPERIMENTAL DATA

Experimental validation of the proposed work is done by applying the model on a set of terrestrial images of the historic monument called Fariabag palace situated at Ahmednagar in Maharashtra, India from a mobile camera. This historic structure was built around 1583 which is an example of Indi-Islamic architecture. The master dataset comprises 30 high-resolution RGB images. Photogrammetry requires overlapping images and hence images are taken so that the points on the surface of the monument are present in more than one image. The original view of the Faribag Palace is shown in Fig 1 and the default photogrammetric reconstruction with the

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test images is shown in Fig 2. The details of the data characteristics are presented in Table 1

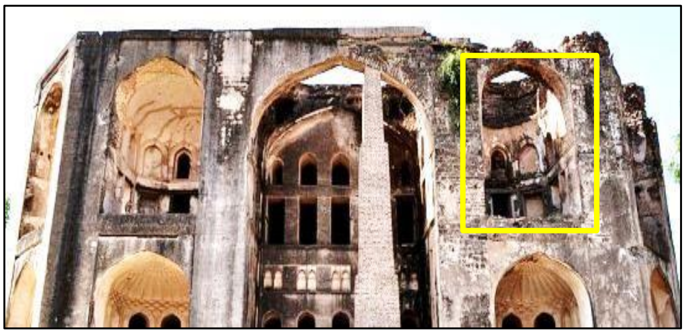

Fig 1. View of Fariabaug Palace

(a) Polygonal Shaded surface (b) Default Textured Surface
Fig 2. Reconstruction for damaged portion of monument using photogrammetry:

Table 1: Data Characteristics

	Property	Value
Image	Dimensions	4000x3000
	Resolution	96dpi
	Bit Depth	24
	Color Compression	sRGB
Camera	Camera Model	Redmi Note 6 Pro
	F-stop	f/1.9
	Exposure	1/324 sec
	ISO speed	1SO-250
	Focal Length	4mm

Higher the number of images, the better the result. However, due to physical restrictions, some portions of the monument has limited visibility in some of the images. This is handled by the estimations using the smoothing approach discussed in this paper. Images were acquired in a restricted space with a variation of around 10m to 15m in the horizontal direction from the source structure. It is in contrast to the ideal requirement of circular movement. As, a complete movement loop is not followed, this making data more constrained. This limitation is overcome by smoothing and interpolation for the set of points obtained during the photogrammetry-based process.

5. FRAMEWORK FOR IMPROVING 3D RECONSTRUCTION

For age-old buildings like historic forts, the techniques like photogrammetry are the preferred method for digital reconstruction, modeling, and visualizing surfaces. Since it is a non-contact-based method, the safety of archeological and historical monuments can be ensured. The general steps in the photogrammetry process include loading and inspecting images, eliminating redundant images; aligning photos; computing dense point clouds; generate 3D polygonal mesh representation and texturize the model. Further if required we can build a titled model and build DEM for exporting results for further processing and visualization. Studies, as discussed in [24], show that opportunities exist at intermediate stages to optimize the missing and noisy data so that the final results are better approximated for surface generation. At this intermediate stage discontinuities in the surface structure also needs attention and must be fused.

The discontinuities and noise in the input are overcome by approximating the surface geometry by data smoothing and interpolation methods. The benefit of using smoothing is experienced when the data is missing due to constraints in acquiring data as in the case of the historical structures and monuments. These monuments are very old and their surface is often in a damaged[21] form. Morphological interpolation [25] can help to bridge the holes and reconstruct the improved surface. This additional smoothing of surface points are integrations in the 3D photogrammetric reconstruction to help in better surface triangulation and thereby the improved final surface.

The proposed framework in Fig 3 for surface reconstruction relies on the number of photographs for optimal photogrammetry. This number can be obtained from the following relation.

$$\frac{L_p}{d} = \frac{C}{F}[1 + (n-1)O_L] \quad \ldots(3)$$

where n is the required number of photographs. L_p and d is the length of the path and distance from the geospatial structure respectively. F is the focal length of the camera, C is CCD in mm and O_L defines the percentage of overlap between the images. The overlap defines and controls the spatial approximation of the generated points in the point cloud. The two approaches viz. the tonal adjustments and morphological improvements for improving the quality of 3D reconstruction are integrated into the proposed framework for improved photogrammetry-based 3D reconstruction workflow shown in Fig 3.

A. Color Tonal Adjustment

After acquiring the set of input images, the images are subject to color tone adjustments[10]. The empirically determined value of brightness is 40% which retains major features of the object contained in the image. The contrast value

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of 0.3 highlights all prominent surface details. These preprocessed sets of images undergo a photogrammetry pipeline and help to generate an optimized dense surface point cloud. This point cloud generates a better surface approximation (See Fig. 4). The improvement has been seen in the depth estimates and thus the hollow window-like structure in the monument. Though the results are better, it can be further improved by morphological smoothing operations on the point cloud before feeding it to the mesh generation and texturing.

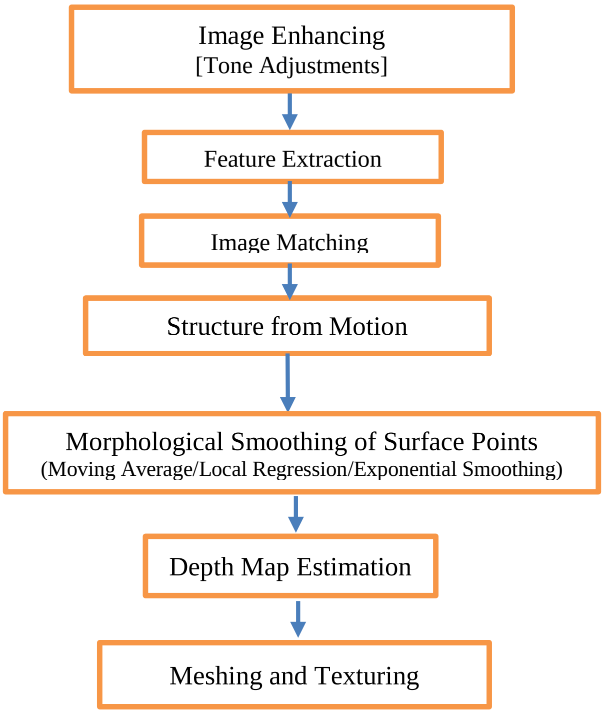


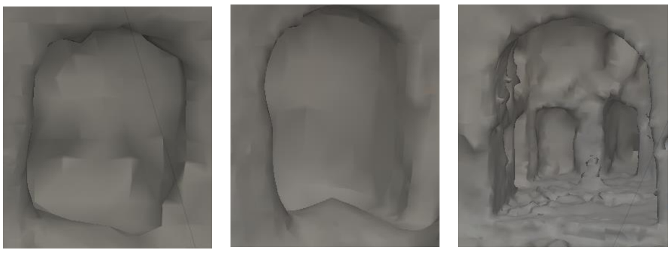
Fig 3: Enhanced Photogrammetric Workflow

Fig 4: Surface after Color tone Adjustment

The point cloud is optimized to address sharp height differences in 3D space which leads to erroneous fused surface details.

B. Improving Quality Point Cloud Smoothening

The generated point cloud visualization was done using PCL and also verified by the software Metashape® Photoscan. Georeferenced coordinates and height for each point are also extracted for each point. Further improvement in the generated surface can be obtained by morphological smoothening of dense cloud generated. Therefore, before generating the final mesh or textured surface, these points are processed for smoothening. These extracted point clouds data is first morphologically smoothened using a moving average (see equation 1) within a predefined radius. The region of the surface with adequate points does not show much variance while regions with missing and noise generate smoothly blended control points.



(a) (b) (c)

Fig 5. Surface quality of damaged portion of the monument: (a) Default Surface (b) After Color Tone Enhancement (c) After Morphological Smoothing(Local Regression)

Fig 6. Surface reconstruction Quality and Performance

A way to improve the surface is through the use of weighted local regression achieves (see equation 2). Exponential can also be applied for local smoothing especially when linear and local assessments are done. (see Equation 3). Finally, the optimized point is taken for surface triangulation [26]. The proposed framework shows significant improvement in the reconstructed surface. For a damaged portion of the monument the quality of the default reconstructed surface, the surface after applying color tone enhancements, and morphological smoothing are shown in Fig 5 respectively. Fig 5c shows the surface point approximation after local regression. The experimental performance of surface approximation and residual error for the number of images sample in the test data set is shown in Fig 6.

6. OBSERVATIONS AND DISCUSSIONS

Theoretically, the good quality reconstruction of the surface is only possible when the geometry is visible from at least two camera positions. For a situation with missing data values when no overlapping or less overlapping between images is available then the reconstruction quality is poor and often erroneous. The proposed framework integrates the tonal adjustments and local smoothing of data points achieves

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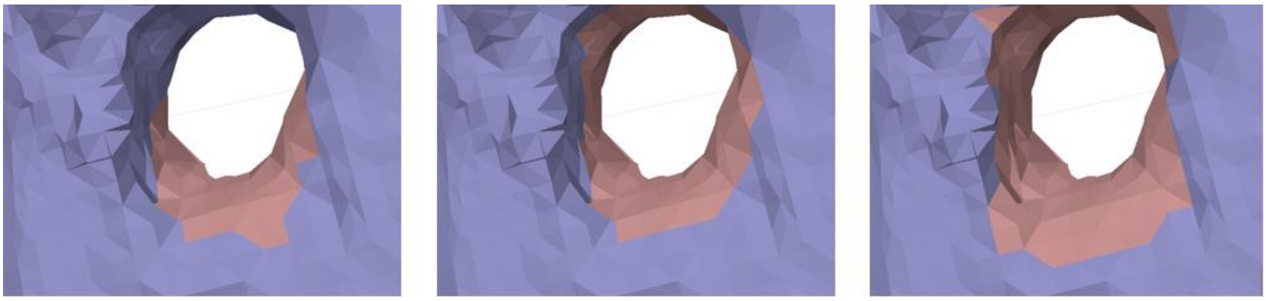

(a) Moving average smothening (b) Exponential smoothing (c) Local Regression smothing

Fig. 7. Optimizing Surface Control Points

(a) moving average smothening (b) Exponential smoothing (c) Local Regression smothing

Fig. 8. Reconstructed Surface for Damaged Portion of Monument

improvements in the final results. The residual error for each of the cases of smoothing is presented in Fig 5. The comparison of resulting predictions and thus the surface approximation suggests that the moving average, Local regression, and exponential smoothing method can improve the reconstruction performance (see Fig. 6) over default results. However, it is to be noted that when the approximation is universal some fine details may be fused to attain the smooth surface transitions.

Local regression-based smoothing operation gives more optimized surface approximation with more fine details of the surface patterns. (see Fig. 7 and Fig 8). The regression weights help in preserving the significant surface variations and help in heuristic predictions on the surface. The method offers the flexibility of using even or odd; symmetric or asymmetric span which is sometimes more useful. The camera location error and overlap have a significant impact on the resulting surface and evident from the reconstructed surface. Relative orientation has a significant impact on the estimation of neighboring points. The assessment of the errors in relative orientation was computed using residuals by variance-covariance metric between the geospatial points obtained through the process described in the framework. The observation for the experimental data is outlined in Table 2 and Table 3 respectively.

The depth estimates are highly influenced by the Z error which is primarily due to camera positioning and orientation besides inadequacy of the number of image frames. Note that fixed position imaging results in restricted spatial and orientation change and therefore becomes a bottleneck during data value prediction. Spatial change in camera position and also orientation results in less error and thus better approximation of the surface values. This validates the requirement of uniform spatial spacing and also incremental change in orientation for better results.

Table 2 Average Camera location error (in m)

X error	Y error	XY error	Z error	Total Error
1.50725	2.01759	2.51843	2.85763	3.80901

Table 3: Output characteristics and coverage

Point Cloud Attributes	Value
Tie Points	11,579 of 19,263
RMS Reprojection Error	0.716567 (2.40576 pix)
Max Reprojection Error	2.21602 (44.1658 pix)
Mean key point size	3.31502 pix
Number of images	104
Ground resolution	2.47 mm/pix
Coverage area	322 sq m
Aligned Camera stations	99
Projections	90,155
Re-projection error	2.41 pix
Effective overlap	8.43467

Some of the other salient observations from the experimentation are described below.

- Improvement in surface quality by applying tonal adjustment is reverified.
- Smoothing of data points helps in the removal of noise from the extracted points, thus enabling the preservation of the prominent features on the surface and culling away unwanted sharp data spikes.
- Moving average allows flexible span but needs only to be odd ordered span. Local regression on the other hand allows the use of symmetric as well as asymmetric weight function and gives more preference to the predictor values. The output is a better approximation, especially with

varying surface elevations. The performance of exponential smoothing lies between the local regression and moving average method.

- The quaity improves with more number of image frames in all three smoothing methods. However the reidual error in least in local regression andhigher for moving average
- Although data smoothing methods can aid in estimating certain surface trends, sometimes it may result in certain data points being overlooked. This may sometimes generate unnecessary approximations.

From a larger perspective, we found that surface point smoothing helps in optimizing surface quality for historical buildings and structures. Combining the tonal adjustments and 3D morphological smoothening of surface points helps to improve the quality of the generated surface for historic structures.

7. CONCLUSION

The use of photogrammetry allows 3D reconstruction of small and large geospatial features. It is validated through experimental observations that photogrammetric results for damaged portions of the surface can be improved by applying smoothing operations. An integrated approach of tonal adjustments on contrast and brightness combined with morphological smoothening of the generated point cloud produces a better approximation of the surface. These adjustments improve the photogrammetry-based models by removing small holes and also reduce large deformations due to the presence of outlier points in the generated point cloud. Local regression is found to be helpful to overcome holes and interpolates points in the region to generate an improved surface approximation besides preserving the overall surface profile. It is also established that aerial triangulation and close-range photography in photogrammetry are useful to compute the 3-dimensional surface coordinates. An integrated framework comprising of morphological improvements together with tonal adjustment can be useful in photogrammetry and provides future pointers to improvements in surface reconstruction and visualization.

REFERENCES

[1] C. T. Silva *et al.*, “A Survey of Surface Reconstruction from Point Clouds,” *Comput. Graph. Forum*, vol. 36, no. 1, pp. 301–329, 2016, doi: 10.1111/cgf.12802.

[2] L. Cheng, Y. Chen, L. Tong, K. Yang, M. Li, and J. Wang, “Multiscale Grid Method for Detection and Reconstruction of Building Roofs from Airborne LiDAR Data,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 7, no. 10, pp. 4081– 4094, 2014, doi: 10.1109/jstars.2014.2306003.

[3] B. Schoen-Phelan, M. Bertolotto, D. F. Laefer, S. W. Corish, B. Schön, and S. W. Morrish, “Storage, Manipulation, and Visualization of LiDAR Data,” pp. 25–28, 2009, Accessed: Jun. 09, 2017. [Online]. Available: http://arrow.dit.ie/scschcomcon.

[4] B. Kovač and B. Žalik, “Visualization of LIDAR datasets using point-based rendering technique,” *Comput. Geosci.*, vol. 36, no. 11, pp. 1443–1450, Nov. 2010, doi:10.1016/J.CAGEO.2010.02.011.

[5] M. M. Houck, F. Crispino, and T. McAdam, “Photogrammetry and 3D Reconstruction,” *Sci. Crime Scenes*, pp. 361–377, 2018, doi: 10.1016/b978-0-12-849878-1.00027-2.

[6] J. Baqersad, P. Poozesh, C. Niezrecki, and P. Avitabile, “Photogrammetry and optical methods in structural dynamics – A review,” *Mech. Syst. Signal Process.*, vol. 86, pp. 17–34, Mar. 2017, doi: 10.1016/J.YMSSP.2016.02.011.

[7] J. S. Aber, I. Marzolff, J. B. Ries, and S. E. W. Aber, “Principles of Photogrammetry,” *Small-Format Aer. Photogr. UAS Imag.*, pp. 19–38, 2019, doi: 10.1016/b978-0-12-812942-5.00003-3.

[8] K. Kingsland, “Comparative analysis of digital photogrammetry software for cultural heritage,” *Digit. Appl. Archaeol. Cult. Herit.*, vol. 18, no. July, p. e00157, 2020, doi: 10.1016/j.daach.2020.e00157.

[9] L. Wang and C. H. H. Chu, “3D building reconstruction from LiDAR data,” *Conf. Proc. - IEEE Int. Conf. Syst. Man Cybern.*, no. October, pp. 3054–3059, 2009, doi: 10.1109/ICSMC.2009.5345938.

[10] S. R. Maurya and G. M. Magar, “Assessing the Impact of Color Adjustments on Photogrammetry-Based 3D Surface Reconstruction,” *Int. J. Comput. Sci. Eng.*, vol. 6, no. 2, pp. 189–195, 2018, doi: 10.26438/ijcse/v6i2.189195.

[11] L. Ragia, F. Sarri, and K. Mania, “3D reconstruction and visualization of alternatives for restoration of historic buildings a new approach,” *GISTAM 2015 - 1st Int. Conf. Geogr. Inf. Syst. Theory, Appl. Manag. Proc.*, pp. 94–102, 2015, doi:10.5220/0005376700940102.

[12] A. C. Carrilho, R. C. Dos Santos, G. G. Pessoa, and M. Galo, “Comparison between airborne lidar data and digital image matching for surface reconstruction,” *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.*, vol. 42, no. 3/W12, pp. 509–514, 2020, doi: 10.5194/isprs-archives-XLII-3-W122020-509-2020.

[13] P. Hu and B. Yang, “Visual perception driven 3D building structure representation from airborne laser

scanning point cloud,” *Virtual Real. Intell. Hardw.*, vol. 2, no. 3, pp. 261–275, 2020, doi: 10.1016/j.vrih.2020.05.004.

[14] S. Wang *et al.*, “Robust 3D reconstruction of building surfaces from point clouds based on structural and closed constraints,” *ISPRS J. Photogramm. Remote Sens.*, vol. 170, no. October, pp. 29–44, 2020, doi: 10.1016/j.isprsjprs.2020.09.004.

[15] M. G. D’Urso, E. Corsi, and C. Corsi, “Mapping of archaeological evidences and 3D models for the historical reconstruction of archaeological sites,” *2018 IEEE Int. Conf. Metrol. Archaeol. Cult. Heritage, MetroArchaeo 2018 - Proc.*, pp. 437–442, 2018, doi: 10.1109/MetroArchaeo43810.2018.9089783.

[16] F. Uygun, M. Hamamcioğlu Turan, and O. Ocali, “Photogrammetric evaluation options of an ancient monument for different survey levels,” *J. Archaeol. Sci. Reports*, vol. 8, pp. 200–205, 2016, doi: 10.1016/j.jasrep.2016.06.020.

[17] J. Fryer and G. Scarmana, “Algorithm Development for the Enhancement of Photogrammetric Digital Images To Improve Dem Generation,” *Int. Arch. Photogramm. …*, no. July, 2002, [Online]. Available: http://www.isprs.org/proceedings/XXXIV/part3/papers/paper002.pdf.

[18] C. Dostal and K. Yamafune, “Photogrammetric texture mapping: A method for increasing the Fidelity of 3D models of cultural heritage materials,” *J. Archaeol. Sci. Reports*, vol. 18, no. January, pp. 430–436, 2018, doi: 10.1016/j.jasrep.2018.01.024.

[19] M. Daakir, Y. Zhou, M. Pierrot Deseilligny, C. Thom, O. Martin, and E. Rupnik, “Improvement of photogrammetric accuracy by modeling and correcting the thermal effect on camera calibration,” *ISPRS J. Photogramm. Remote Sens.*, vol. 148, no. January 2018, pp. 142–155, 2019, doi:10.1016/j.isprsjprs.2018.12.012.

[20] P. Sapirstein, “A high-precision photogrammetric recording system for small artifacts,” *J. Cult. Herit.*, vol. 31, pp. 33–45, 2018, doi: 10.1016/j.culher.2017.10.011.

[21] F. F. Rosella Alessia Galantucci, “Advanced damage detection techniques in historical buildings using digital photogrammetry and 3D surface anlysis,” *J. Cult. Herit.*, vol. 36, pp. 51–62, 2019, doi: https://doi.org/10.1016/j.culher.2018.09.014.

[22] S. Dawn and P. Biswas, *Technologies and methods for 3D reconstruction in archaeology*, vol. 968, no. i. Springer Singapore, 2019.

[23] R. Veerabhadra, “A Simple Introduction to Moving Least Squares and Local Regression Estimation,” 2017. doi: 10.2172/1367799.

[24] A. Ballabeni and M. Gaiani, “Intensity histogram equalisation, a colour-to-grey conversion strategy improving photogrammetric reconstruction of urban architectural heritage,” *J. Int. Colour Assoc.*, vol. 16, pp. 2–23, 2016, Accessed: Jan. 19, 2018. [Online]. Available: http://www.aiccolour.org/journal.htm.

[25] R. K. Maurya, S. T. Kulkarni, and N. Kalita, “Projection-based spatial morphology for extracting ridge and valley profiles of mountains from 3D amorphous data,” in *2018 4th International Conference on Computing Communication and Automation, ICCCA 2018*, Dec. 2018, pp. 1–6, doi: 10.1109/CCAA.2018.8777680.

[26] S. R. Maurya and G. M. Magar, “Performance of Greedy Triangulation Algorithm on Reconstruction of Coastal Dune Surface,” in *2018 3rd International Conference for Convergence in Technology (I2CT)*, Apr. 2018, pp. 1–6, doi:10.1109/I2CT.2018.8529765.

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