December, 2021 Vol.5 No.10 22-31

3D Reconstruction and Texture Refinement with Image Enhancement for Improved Visual Quality

Reconstrucción 3D y refinamiento de texturas con mejora de la imagen para mejorar la calidad visual

CORONA-PATRICIO, Cesar Agustin†[1] & RETA, Carolina*[2]

[1]*CONACYT-CIATEQ A. C. PICYT. San Agustín del Retablo 150, Constituyentes Fovissste, C.P. 76150 Santiago de Queretaro, Qro., Mexico*
[2]*CONACYT-CIATEQ A. C. Department of IT, Control, and Electronics. Manzana 5, Lote 1, entre Gaza 30 y 40, C.P. 42162 San Agustin Tlaxiaca, Hgo., Mexico*

ID 1st Author: *Cesar Agustin Corona-Patricio* / **ORC ID:** 0000-0002-9105-9483, **CVU CONACYT ID**: 874048

ID 1st Co-author: *Carolina, Reta* / **ORC ID**: 0000-0002-0843-129X, **CVU CONACYT ID**: 235176

DOI: 10.35429/EJT.2021.10.5.22.31 Received July 22, 2021; Accepted December 30, 2021

Abstract

This paper proposes a method to generate surface and texture models from rigid objects captured with an RGB-D camera. The method integrates five stages: 1. Point cloud generation from RGB-D images; 2. Surface model generation; 3. Surface model refinement; 4. Texture generation and mapping; 5. Texture enhancement. The use of image processing algorithms for texture enhancement and the refinement of the surface models enables the improvement of the appearance of reconstructed models. The performed experimentation shows the results of the proposed method for five small textured objects. The appearance of reconstructed models was evaluated using a visual quality index; a sharper texture helps to improve such index.

3D reconstruction, Point cloud, Surface models, Textured models, Texture mapping, Image enhancement

Resumen

En este trabajo se propone un método para generar modelos de superficie y de textura de objetos rígidos capturados con una cámara RGB-D. El método propuesto integra cinco etapas: 1. Generación de nube de puntos a partir de imágenes RGB-D; 2. Generación de modelo de superficie; 3. Refinamiento de modelo de superficie; 4. Generación y mapeo de textura; 5. Mejora de textura. El uso de algoritmos de procesamiento de imágenes para la afinación de textura en conjunto con el refinamiento de los modelos de superficie permite mejorar la apariencia de los modelos reconstruidos. La experimentación realizada muestra los resultados del método propuesto utilizado en la reconstrucción de cinco objetos pequeños ricos en textura. Se evaluó la apariencia del modelo reconstruido mediante un índice de la calidad visual; se comprobó que una textura con mayor nitidez ayuda a mejorar dicho índice.

Reconstrucción 3D, Nube de puntos, Modelos de superficie, Modelos texturizados, Mapeo de textura, Mejoramiento de imágenes

Citation: CORONA-PATRICIO, Cesar Agustin & RETA, Carolina. 3D Reconstruction and Texture Refinement with Image Enhancement for Improved Visual Quality. ECORFAN Journal-Taiwan. 2021. 5-10: 22-31

* Author Correspondence (e-mail: carolina.reta@ciateq.mx)
† Researcher contributing as first author.

1. Introduction

In 3D reconstruction, obtaining textured models is a research topic of interest, particularly in virtual, augmented, and mixed reality applications; it is desired that digital models have an appearance as close as possible to the real object. Different factors influence the appearance of the digitalized models, such as the refinement of the reconstructed geometric surface and the quality of its color texture. The surface can be refined using algorithms that remove noise and other elements that are not part of the object to be reconstructed, as well as algorithms to fill in missing parts of the surface that could not be reconstructed due to a lack of information in the point cloud. The visual appearance of the model can be improved by applying image sharpening algorithms.

In our previous work (Corona & Reta, 2021), a systematized process for capturing a rigid object with an RGB-D was proposed. This work presents a 3D reconstruction method for generating textured models from a set of RGB-D images captured from different viewpoints of small objects, which comprises:

- An algorithm to generate a point cloud from RGB-D images.
- A surface reconstruction method from point clouds to generate a surface model represented as a polygon mesh.
- A surface refinement algorithm to remove noise, fill missing parts, and simplify the surface model.
- A texture mapping method to generate textured models from the acquired color images.
- An image processing approach for texture enhancement.

A summary of theoretical concepts and relevant works in the literature for the generation of surface and texture models is presented below.

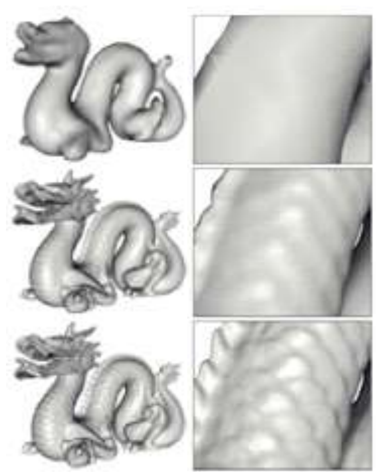
1.1 Acquisition of multiple RGB-D images and generation of point cloud

The acquisition of RGB-D images can be carried out as proposed in (Corona & Reta, 2021) where, by means of a positioning machine, a stereoscopic camera is moved in such a way that visual characteristics of an object can be obtained from different points of view.

This is to acquire the necessary information of the object for its 3D reconstruction. The reconstruction of objects starts with a process in which a geometric structure is obtained, that can be organized as a structured set of points in space, also known as a point cloud. There are different image-based reconstruction methods to generate point clouds. Some of these methods are based on visual odometry (VO) and simultaneous localization and mapping (SLAM). It is also possible to use a stereoscopic camera to perform the 3D reconstruction in real-time.

1.2 Generation of surface models

A surface model is a geometric model of a surface that describes the shape of some object or scene (Fisher et al., 2016). A mesh is a bounded surface formed by flat faces and edges that form polygons (Fisher et al., 2016). In Figure **1**, a surface model is shown.



a) b)

Figure 1 Surface model represented as a mesh with different levels of resolution generated by Poisson Reconstruction method. a) Geometric model where the geometric detail is increased. b) Section of the model where the increase in geometric detail can be seen
Source (Kazhdan et al., 2013)

To make a 3D reconstruction, one or more images can be used. In the case of using a single depth image known as RGB-D or traditional color images (RGB) as in (Zhang & Funkhouser, 2018), (Sun et al., 2018), (B. Yang et al., 2018), and (J. Wang et al., 2018), Deep Learning methods can be used to generate a surface or point cloud. With Deep Learning methods, acceptable results are obtained when reconstructing simple objects.However, they have not been used in the 3D reconstruction of real objects.

For 3D reconstruction, some methods generate the surface from a point cloud constructed from RGB-D images. This reconstruction can be without texture mapping (F. Wang & Hauser, 2019), (Sheng et al., 2018), (Tzionas & Gall, 2015), (Gao et al., 2019), (K. Wang et al., 2014), (Zhong et al., 2019), (Mi et al., 2020), and (Kazhdan et al., 2013) or with texture mapping (Vrubel et al., 2009) and (Tucci et al., 2012). Some methods use a priori templates (Hao et al., 2019). Models reconstructed with templates look aesthetically better, but in applications such as inspection, their use is not recommended because information about the true geometry of the object is lost.

Some techniques for eliminating problems that affect reconstruction quality are the use of feedback with algorithms for visual odometry such as SLAM (Deris et al., 2017), (Y. Yang et al., 2019), (Civera & Lee, 2019), and (Huang et al., 2020) and inertial measurement units or IMUs (Pintore et al., 2020), which enable the reconstruction to be carried out in real-time. The techniques for improving the quality of reconstruction using denoising algorithms (Almonacid et al., 2018), (Mi & Tao, 2018), (Sterzentsenko et al., 2019), (Jia et al., 2019), and (Wolff et al., 2016) and the algorithms for completing missing parts in the surface (Centin & Signoroni, 2018), (Lin et al., 2017), (Xia & Zhang, 2017), and (Centin et al., 2015).

1.3 Generation of textured models

A textured model is a surface model to which a texture is applied in order to give it the appearance of a real object.
Figure **2** shows the difference between a surface model without texture and a surface model rendered with texture.

Figure 2 a) Surface model. b) Surface model rendered with texture
Source (Waechter et al., 2014)

It is possible to create a textured model using a single image using deep learning methods (J. Wang et al., 2019), (Lazova et al., 2019), and (Henderson et al., 2020). However, the obtained results do not have a photorealistic finish; better results can be obtained with reconstruction methods based on multiple views without using artificial intelligence (Nunes Masson & Petry, 2019).

1.4 Techniques for texture enhancement

In (W. Li et al., 2019), (Kim et al., 2019), (Fu et al., 2018), and (Rouhani et al., 2018), texture optimization techniques have been adopted to improve the quality of the final texture, reducing ghosting and blurring problems. More recently, Deep Learning techniques have been adopted (Huang et al., 2020), (Richard et al., 2020), (Y. Li et al., 2019), and (Wu et al., 2019), with which results outperform the quality of previous methods.

Textures of a model can be generated synthetically using artificial intelligence techniques from multiple images (Raj et al., 2019). Synthetic textures typically do not provide a realistic finish since lighting and shadow information is lost.

This work proposes a method based on image processing, in conjunction with surface refinement, to reconstruct objects, giving them a better visual appearance. The goal is to reduce human intervention during the reconstruction process by reducing the required time and automating the process of digitizing objects.

This paper is organized as follows. Section 2 proposes the method for generating textured models, including point cloud generation, surface reconstruction, and texture mapping and enhancement. Section 3 presents the visual results of the generated models. Finally, Section 4 presents the conclusions of the proposed work and discusses future work.

2. Proposed method

The proposed method consists of generating a textured model of a rigid object, using the information captured with a set of images taken from different positions around this object. Figure 3 presents the steps of the proposed method.

It starts from a set of previously acquired RGB-D images; from these images multiple point clouds are generated, which are aligned and merged into a single one. This point cloud is processed to generate a surface as a polygonal mesh, which is refined to eliminate imperfections that affect the quality of the appearance; after that, texture mapping is performed on this surface; then, by means of image processing algorithms, texture enhancement is performed to improve the visual appearance of the textured model. The visual appearance is evaluated using a perceptual visual quality metric (Crété-Roffet et al., 2007). Finally, the textured model is exported in a digital format so that it can be integrated into mixed reality applications.

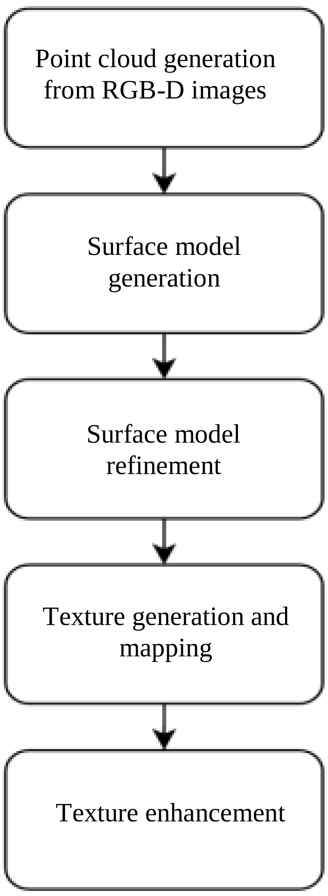


Figure 3 Proposed method
Source: Own Elaboration

In this work, a method based on image processing algorithms is proposed to improve the appearance of the textured models. An evaluation metric was adopted to objectively measure the visual quality of the reconstructed models, in order to determine if an improvement in the visual quality index can be obtained using the proposed method.

2.1 Data capture

Multiple images were captured to obtain different views of the object. One way to capture them is proposed in (Corona & Reta, 2021), where a camera rotates around a fixed object to take images from different viewpoints. In this work, RGB-D images were captured with a StereoLabs ZED stereo camera (Stereolabs, 2021) using its API (Stereolabs, 2021), and previously calibrated with the proprietary SDK (Stereolabs, 2021). The capture is performed indoors under controlled lighting conditions, and using fixed light sources pointing towards the object; this provides the appropriate illumination levels to obtain sharp images. Depending on the object to be digitalized, the camera parameters and the number of images to be captured are modified.

2.2 Surface reconstruction

For surface generation, the Open3D library is used (Zhou et al., 2018). The captured RGB-D images are used to generate multiple point clouds from them; the point clouds are aligned using the multiway registration process proposed in Open3D. This process is based on a global registration method and allows multiple point clouds to be aligned simultaneously. During the alignment process, the point clouds are merged with Open3D using an addition operator. The resulting merged point cloud is used to generate a surface using the ball pivoting reconstruction method included in Open3D, with which the surface model is obtained.

2.3 Surface refinement

Surface refinement is performed using the Open3D library (Zhou et al., 2018) and the PyMeshFix library (Kaszynski, 2020). The polygonal mesh obtained in the previous stage is processed with an average filter included in Open3D to reduce the noise and smooth the surface; with the connected components method, the mesh is grouped into clusters, and non-connected components are eliminated from this mesh. To fill missing parts in the mesh, the PyMeshFix library is used, which takes the mesh as input and returns a new mesh without holes. Finally, to eliminate faces of the polygonal mesh that do not provide relevant geometric information and to reduce processing time in subsequent processes, the mesh decimation method included in Open3D for mesh simplification is applied.

ISSN 2524-2121

The refinement of the polygonal mesh will always be carried out in each reconstruction process, assuming that the mesh presents some defect; in case it does not present any defect, after the refinement, an unaltered mesh will be obtained.

2.4 Texture generation and mapping

With the RGB images, a texture image is generated and mapped onto the surface of the polygonal mesh. A Python library available on GitHub (Iory, 2020), based on the Point Cloud Library (Rusu & Cousins, 2011), is used to do the texture mapping. Texture mapping is done using a warping-based mapping method; the camera calibration matrix and the rotation and translation matrices for each position are used to map the images on the surface.

2.5 Texture enhancement

Using a method based on image processing algorithms, a new texture is generated for the surface model, which provides an improvement in the appearance of the textured models with respect to a perceptible visual quality index.

For texture enhancement, a sharpening filter included in the library PIL (Crété-Roffet et al., 2007) is used. To apply this filter, the previously generated textures are taken as input; after processing the textures using the sharpening filter, the output images are exported and used as the new textures for the surface models.

3. Results

From figure 4 to figure 8 , visual results are presented for the stages of the proposed method to obtain the textured surface models using five test objects. In *a,* the RGB color images are represented; in *b,* the depth images; in *c,* the point cloud generated from the depth images; in *d,* the reconstructed surface from the point cloud; in *e,* the refined surface where filters were applied to remove noise and fill holes; in *f*, the textured surface model, where RGB textures were enhanced and mapped onto the refined surface.

Figure 4 shows the results of the proposed method for generating a textured model of a sculpture with homogeneous textures and a slightly reflective surface.

After refinement of the surface model (see *e*), it can be seen that an accurate representation of the geometry of the real object was not obtained. However, by applying the texture (see *f*), it can be seen that the texture helps compensate for the lack of detail of the surface model, providing an appearance closer to the real object.

Figure 5 hows the generation of a textured model of a box with a non-reflective surface and rich in texture. In *g*, it can be observed that the obtained textured surface model looks similar to the original object.

Figure 6 shows the generation of a textured model of a box with a slightly reflective surface and rich in texture. Similar to the box shown in Figure 6, a model with a blurred and misaligned texture was obtained (see *g*). The corrective actions to be taken in the texture optimization stage can reduce these problems to improve the appearance of the object model.

Figure 7 shows the generation of a textured surface model of a poorly textured pillar-shaped object. Due to the small size of the object, problems were encountered in acquiring a significant amount of its detail.

Figure 8 shows the generation of a textured surface model of an object with a non-reflective and poorly textured surface. In d, it can be seen that the object of interest has holes in its surface; this error is corrected later in the refinement stage (see e).

Figure 9 shows the differences in texture appearance when using image processing algorithms to improve image sharpness.

3.1 Visual results of textured models

The obtained textured model is evaluated for its appearance quality. The evaluation is carried out quantitatively using a visual quality metric (Crété-Roffet et al., 2007). This evaluation allows determining if the proposed method based on image processing algorithms improves the appearance of texture models.

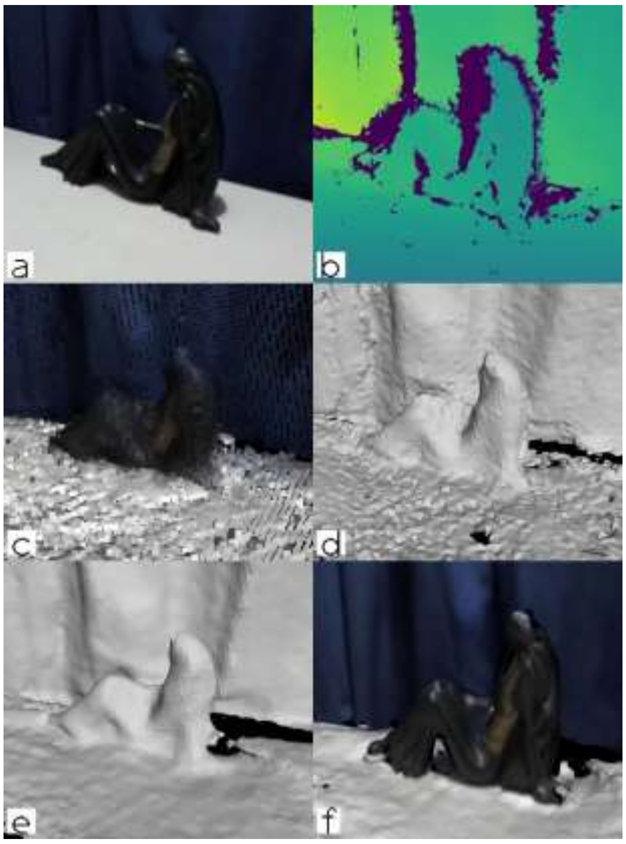


Figure 4 Results of proposed method with Object 1 Sculpture
Source: Own Elaboration

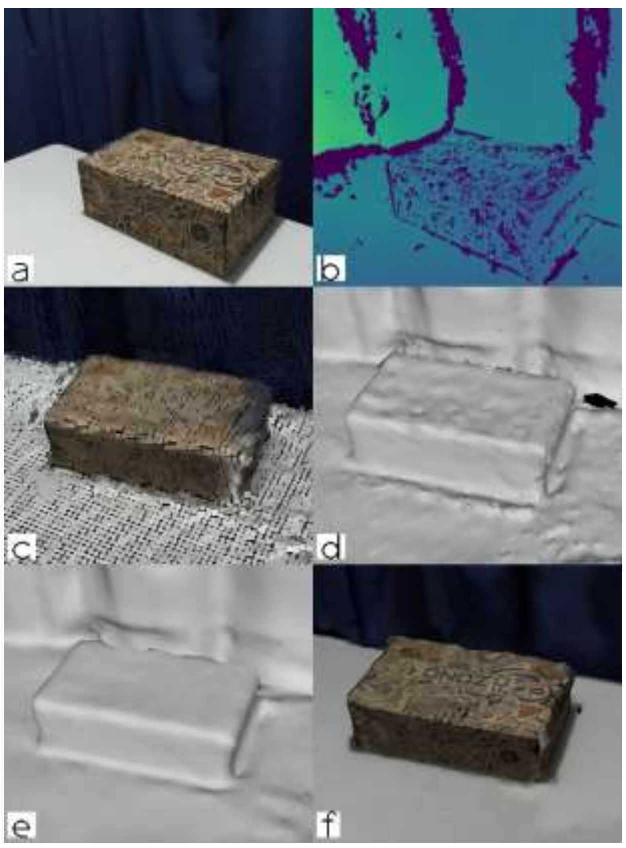


Figure 5 Results of proposed method with Object 2 Ozono Box
Source: Own Elaboration

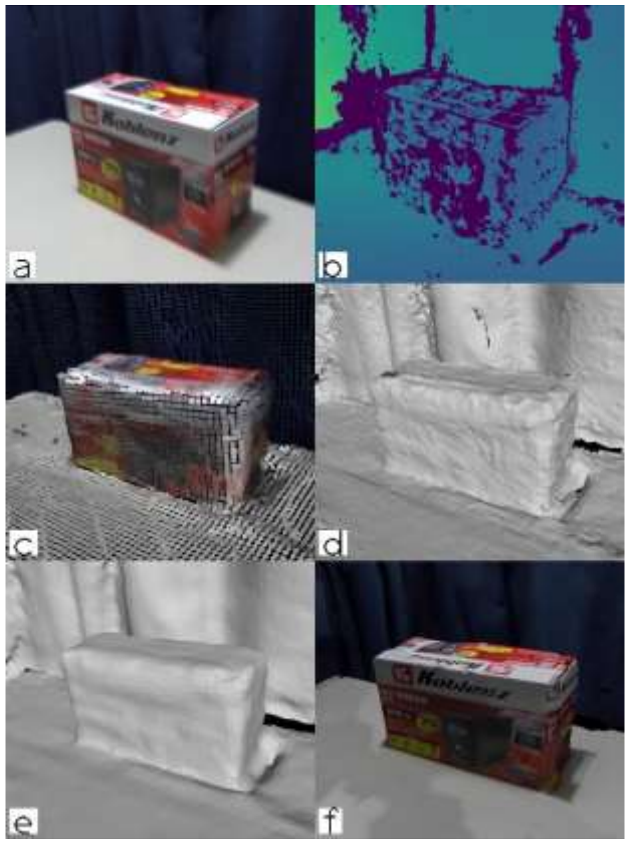


Figure 6 Results of proposed method with Object 3 Koblenz Box
Source: Own Elaboration

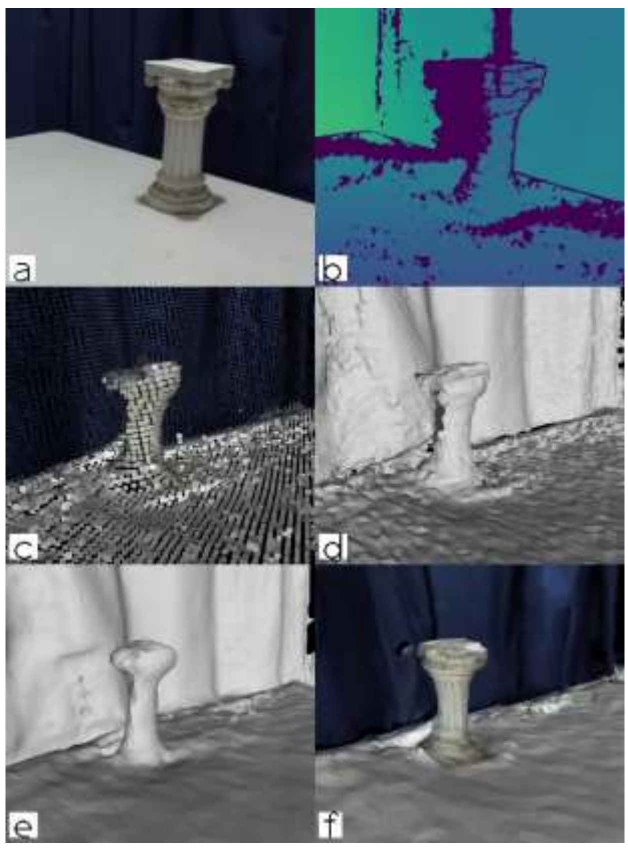


Figure 7 Results of proposed method with Object 4 Pillar
Source: Own Elaboration

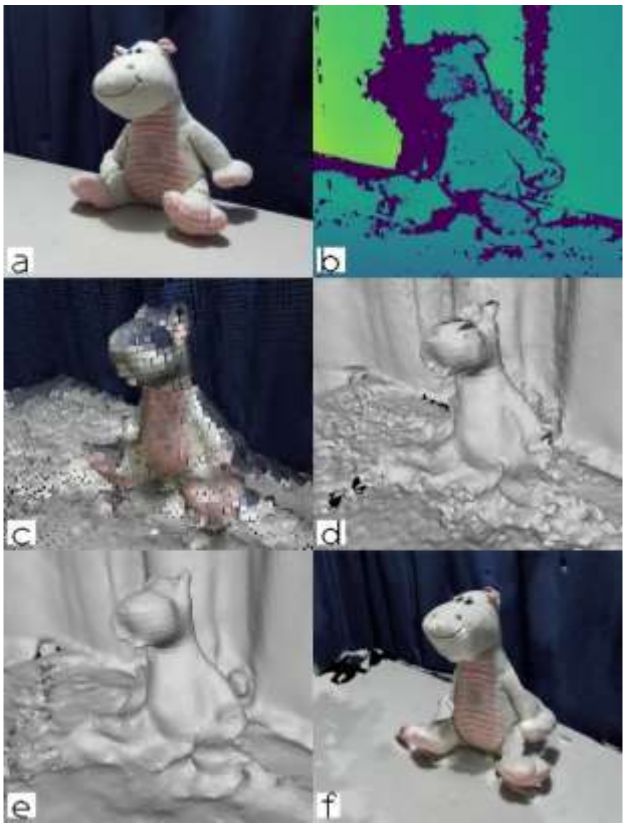


Figure 8 Results of proposed method with Object 5 Hippopotamus
Source: Own Elaboration

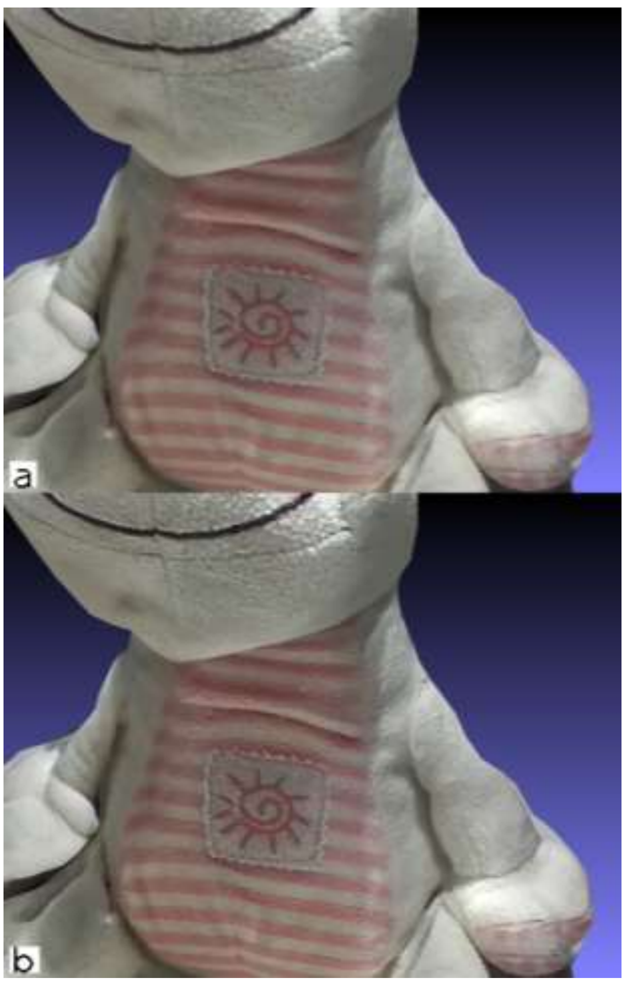


Figure 9 Results of the image processing approach for texture enhancement. a) Reconstructed model with initial texture. b) Reconstructed model after texture enhancement
Source: Own Elaboration

3.2 Evaluation of textured models

A non-reference visual quality index (Crété-Roffet et al., 2007) is used for evaluating the quality of the textures quantitatively. The enhanced textures are converted into grayscale images and then evaluated using the visual metric, resulting in a score from 0 to 1. A lower value indicates the image is sharper, and a higher value that the image is blurrier. As can be observed in Table 1, after using image processing algorithms for the texture enhancement the visual quality index of the textures improved in all models.

	Original texture (blur effect)	Enhanced texture (blur effect)
Object 1	0.31715476	0.28563593
Object 2	0.33325025	0.29602264
Object 3	0.32718573	0.29232520
Object 4	0.31324932	0.28720994
Object 5	0.32300263	0.28698927

Table 1 Visual quality index for original textures and enhanced textures
Source: Own Elaboration

4. Conclusions

This work proposes a method for generating textured models of rigid objects. The proposed method considers stages for point cloud generation from RGB-D images, surface generation and refinement, and texture mapping and enhancement. In the experimentation, it was possible to obtain an acceptable reconstruction in most of the test models, except for Object 4 Pillar, which is too small. The results showed that employing image processing algorithms for image enhancement allows improving the appearance of the textures of the reconstructed models based on the visual quality index used.

Obtaining an improved appearance for the reconstructed models will speed up the production of digital objects in applications where the visual appearance plays a more important role than their geometry, reducing the cost and time of reconstruction compared to methods that require human intervention.

As future work, we envisage the use of different techniques based on Deep Learning for image enhancement, including deblurring and super-resolution techniques, which allow for comparison of the results and look for more improvements in the visual quality of the reconstructed 3D models.

References

Almonacid, J., Cintas, C., Derieux, C., & Lewis, M. (2018). Point Cloud Denoising using Deep Learning. 2018 Congreso Argentino de Ciencias de La Informática y Desarrollos de Investigación (CACIDI), 1–5. https://doi.org/10.1109/CACIDI.2018.8584185

Centin, M., & Signoroni, A. (2018). Advancing mesh completion for digital modeling and manufacturing. Computer Aided Geometric Design, 62, 73–90. https://doi.org/10.1016/j.cagd.2018.03.016

Centin, M., Pezzotti, N., & Signoroni, A. (2015). Poisson-driven seamless completion of triangular meshes. Computer Aided Geometric Design, 35–36, 42–55. https://doi.org/10.1016/j.cagd.2015.03.006

Civera, J., & Lee, S. H. (2019). RGB-D Odometry and SLAM. In P. L. Rosin, Y.-K. Lai, L. Shao, & Y. Liu (Eds.), RGB-D Image Analysis and Processing (pp. 117–144). Springer International Publishing. https://doi.org/10.1007/978-3-030-28603-3_6

Corona, C. A., & Reta, C. (2021). Design of the operation of a rotating machine for the acquisition of multi-view stereoscopic images for the 3D reconstruction of objects. Computational Technologies. 8. https://doi.org/10.35429/JOCT.2021.15.5.29.36

Crété-Roffet, F., Dolmiere, T., Ladret, P., & Nicolas, M. (2007). The Blur Effect: Perception and Estimation with a New No-Reference Perceptual Blur Metric. SPIE Electronic Imaging Symposium Conf Human Vision and Electronic Imaging, XII, EI 6492-16. https://hal.archives-ouvertes.fr/hal-00232709

Deris, A., Trigonis, I., Aravanis, A., & Stathopoulou, E. (2017). DEPTH CAMERAS ON UAVs: A FIRST APPROACH. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-2/W3, 231–236. https://doi.org/10.5194/isprs-archives-XLII-2-W3-231-2017

Fisher, R. B., Breckon, T. P., Dawson-Howe, K., Fitzgibbon, A., Robertson, C., Trucco, E., & Williams, C. K. I. (2016). R. In Dictionary of Computer Vision and Image Processing (pp. 228–244). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119286462.ch19

Fu, Y., Yan, Q., Yang, L., Liao, J., & Xiao, C. (2018). Texture Mapping for 3D Reconstruction with RGB-D Sensor. 4645–4653. https://doi.org/10.1109/CVPR.2018.00488

Gao, Y., Yao, Y., & Jiang, Y. (2019). Multi-target 3D Reconstruction from RGB-D Data. 184–191. https://doi.org/10.1145/3339363.3339395

Hao, L., Huang, X., & Li, S. (2019). Surface reconstruction based on CAD model driven priori templates. Review of Scientific Instruments, 90(12), 125116. https://doi.org/10.1063/1.5127224

Henderson, P., Tsiminaki, V., & Lampert, C. H. (2020). Leveraging 2D Data to Learn Textured 3D Mesh Generation. ArXiv:2004.04180 [Cs]. http://arxiv.org/abs/2004.04180

Huang, J., Thies, J., Dai, A., Kundu, A., Jiang, C. M., Guibas, L., Nießner, M., & Funkhouser, T. (2020). Adversarial Texture Optimization from RGB-D Scans. ArXiv:2003.08400 [Cs]. http://arxiv.org/abs/2003.08400

Iory (2020). GitHub. “texture-mapping, PCL Texture Mapping wrapper”. [Online]. Available at: https://github.com/iory/texture-mapping

Jia, C., Yang, T., Wang, C., Fan, B., & He, F. (2019). A new fast filtering algorithm for a 3D point cloud based on RGB-D information. PLOS ONE, 14(8), e0220253. https://doi.org/10.1371/journal.pone.0220253

Kaszynski, A. (2020). “pymeshfix”. [Online]. Available at: https://pypi.org/project/pymeshfix/
Kazhdan, M., Bolitho, M., & Hoppe, H. (2013). Poisson surface reconstruction. ACM Trans. Graph, 32, 1–13.

Kim, J., Kim, H., Park, J., & Lee, S. (2019). Global Texture Mapping for Dynamic Objects. Computer Graphics Forum, 38(7), 697–705. https://doi.org/10.1111/cgf.13872

Lazova, V., Insafutdinov, E., & Pons-Moll, G. (2019). 360-Degree Textures of People in Clothing from a Single Image. ArXiv: 1908.07117 [Cs]. http://arxiv.org/abs/1908.07117

Li, W., Xiao, X., & Hahn, J. (2019). 3D Reconstruction and Texture Optimization Using a Sparse Set of RGB-D Cameras. 1413–1422. https://doi.org/10.1109/WACV.2019.00155

Li, Y., Tsiminaki, V., Timofte, R., Pollefeys, M., & van Gool, L. (2019). 3D Appearance Super-Resolution with Deep Learning. ArXiv: 1906.00925 [Cs]. http://arxiv.org/abs/1906.00925

Lin, S.-C., Shih, T. K., & Hsu, H.-H. (2017). Filling holes in 3D scanned model base on 2D image inpainting. 2017 10th International Conference on Ubi-Media Computing and Workshops (Ubi-Media), 1–6. https://doi.org/10.1109/UMEDIA.2017.8074082

Mi, Z., & Tao, W. (2018). Point Cloud Noise and Outlier Removal with Locally Adaptive Scale. In J.-H. Lai, C.-L. Liu, X. Chen, J. Zhou, T. Tan, N. Zheng, & H. Zha (Eds.), Pattern Recognition and Computer Vision (pp. 415–426). Springer International Publishing. https://doi.org/10.1007/978-3-030-03338-5_35

Mi, Z., Luo, Y., & Tao, W. (2020). SSRNet: Scalable 3D Surface Reconstruction Network. ArXiv: 1911.07401 [Cs]. http://arxiv.org/abs/1911.07401

Nunes Masson, J. E., & Petry, M. R. (2019). Comparison of Algorithms for 3D Reconstruction. 2019 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), 1–6. https://doi.org/10.1109/ICARSC.2019.8733610

Pintore, G., Mura, C., Ganovelli, F., Fuentes-Perez, L. J., Pajarola, R., & Gobbetti, E. (2020). State-of-the-art in Automatic 3D Reconstruction of Structured Indoor Environments. https://doi.org/10.1111/cgf.14021

Raj, A., Ham, C., Barnes, C., Kim, V., Lu, J., & Hays, J. (2019). Learning to Generate Textures on 3D Meshes. 32–38. https://openaccess.thecvf.com/content_CVPRW_2019/html/3DWidDGET/Amit_Raj_Learning_to_Generate_Textures_on_3D_Meshes_CVPRW_2019_paper.html

Richard, A., Cherabier, I., Oswald, M. R., Tsiminaki, V., Pollefeys, M., & Schindler, K. (2020). Learned Multi-View Texture Super-Resolution. ArXiv: 2001.04775 [Cs]. http://arxiv.org/abs/2001.04775

Rouhani, M., Baillard, C., & Fradet, M. (2018, September 5). A Multi-Resolution Approach for Color Correction of Textured Meshes. https://doi.org/10.1109/3DV.2018.00019

Rusu, R., & Cousins, S. (2011). 3D is here: Point Cloud Library (PCL). 2011 IEEE International Conference on Robotics and Automation, 1-4.

Sheng, B., Zhao, F., Yin, X., Zhang, C., Wang, H., & Huang, P. (2018). A Lightweight Surface Reconstruction Method for Online 3D Scanning Point Cloud Data Oriented toward 3D Printing [Research Article]. Mathematical Problems in Engineering; Hindawi. https://doi.org/10.1155/2018/4673849

Stereolabs. (2021). “API Documentation”. [Online]. Available at: https://www.stereolabs.com/docs/api/

Stereolabs. (2021). “ZED SDK 3.5.0”. [Online]. Available at: https://www.stereolabs.com/developers/release/

Stereolabs. (2021). “ZED Stereo Camera | Stereolabs”. [Online]. Available at: https://www.stereolabs.com/zed/

Sterzentsenko, V., Saroglou, L., Chatzitofis, A., Thermos, S., Zioulis, N., Doumanoglou, A., Zarpalas, D., & Daras, P. (2019). Self-Supervised Deep Depth Denoising. ArXiv: 1909.01193 [Cs]. http://arxiv.org/abs/1909.01193

Sun, Y., Liu, Z., Wang, Y., & Sarma, S. E. (2018). Im2Avatar: Colorful 3D Reconstruction from a Single Image. ArXiv: 1804.06375 [Cs]. http://arxiv.org/abs/1804.06375

Tucci, G., Cini, D., & Nobile, A. (2012). Effective 3D digitization of archaeological artifacts for interactive virtual museum. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 38, 413–420. https://doi.org/10.5194/isprsarchives-XXXVIII-5-W16-413-2011

Tzionas, D., & Gall, J. (2015). 3D Object Reconstruction from Hand-Object Interactions. Proceedings / IEEE International Conference on Computer Vision. IEEE International Conference on Computer Vision. https://doi.org/10.1109/ICCV.2015.90

Vrubel, A., Bellon, O., & Silva, L. (2009). A 3D reconstruction pipeline for digital preservation. 2687–2694. https://doi.org/10.1109/CVPR.2009.5206586

Waechter, M., Moehrle, N., & Goesele, M. (2014). Let There Be Color! Large-Scale Texturing of 3D Reconstructions. In D. Fleet, T. Pajdla, B. Schiele, & T. Tuytelaars (Eds.), Computer Vision – ECCV 2014 (pp. 836–850). Springer International Publishing. https://doi.org/10.1007/978-3-319-10602-1_54

Wang, F., & Hauser, K. (2019). In-hand Object Scanning via RGB-D Video Segmentation. 3296–3302. https://doi.org/10.1109/ICRA.2019.8794467

Wang, J., Sun, B., & Lu, Y. (2018). MVPNet: Multi-View Point Regression Networks for 3D Object Reconstruction from A Single Image. ArXiv: 1811.09410 [Cs]. http://arxiv.org/abs/1811.09410

Wang, J., Zhong, Y., Li, Y., Zhang, C., & Wei, Y. (2019). Re-Identification Supervised Texture Generation.

Wang, K., Zhang, G., & Bao, H.-J. (2014). Robust 3D reconstruction with an RGB-D camera. IEEE Transactions on Image Processing : A Publication of the IEEE Signal Processing Society, 23. https://doi.org/10.1109/TIP.2014.2352851

Wolff, K., Kim, C., Zimmer, H., Schroers, C., Botsch, M., Sorkine-Hornung, O., & Sorkine-Hornung, A. (2016). Point Cloud Noise and Outlier Removal for Image-Based 3D Reconstruction. 2016 Fourth International Conference on 3D Vision (3DV), 118–127. https://doi.org/10.1109/3DV.2016.20

Wu, J., Chen, H., Liu, X., Cao, L., Peng, X., & Jin, G. (2019). Unsupervised texture reconstruction method using bidirectional similarity function for 3-D measurements. Optics Communications, 439. https://doi.org/10.1016/j.optcom.2019.01.051

Xia, C., & Zhang, H. (2017). A fast and automatic hole-filling method based on feature line recovery. Computer-Aided Design and Applications, 14, 1–9. https://doi.org/10.1080/16864360.2017.1287677

Yang, B., Rosa, S., Markham, A., Trigoni, N., & Wen, H. (2018). 3D Object Dense Reconstruction from a Single Depth View. IEEE Transactions on Pattern Analysis and Machine Intelligence, PP. https://doi.org/10.1109/TPAMI.2018.2868195

Yang, Y., Dong, W., & Kaess, M. (2019). Surfel-Based Dense RGB-D Reconstruction With Global And Local Consistency. 2019 International Conference on Robotics and Automation (ICRA), 5238–5244. https://doi.org/10.1109/ICRA.2019.8794355

Zhang, Y., & Funkhouser, T. (2018). Deep Depth Completion of a Single RGB-D Image. ArXiv: 1803.09326 [Cs]. http://arxiv.org/abs/1803.09326

Zhong, D.-Y., Zhang, J., & Wang, L. (2019). Fast Implicit Surface Reconstruction for the Radial Basis Functions Interpolant. Applied Sciences, 9, 5335. https://doi.org/10.3390/app9245335

Zhou, Q., Park, J., & Koltun, V. (2018). "Open3D: A Modern Library for 3D Data Processing". ArXiv, abs/1801.09847.