Comparing inpainting techniques for urban object restoration from orbital images

Eduardo Soares Nascimento [1], Allan Alves Lopes Ferreira [1], Guilherme Pina Cardim [2], Pedro Pina [3], Erivaldo Antonio da Silva [1]

[1] Postgraduate Program in Cartographic Sciences (PPGCC), Department of Cartography, School of Technology and Sciences São Paulo State University (FCT-UNESP), 19060-900 Presidente Prudente, São Paulo, Brazil. (e.nascimento, aal.ferreira, erivaldo.silva)@unesp.br
[2] Engineering Department, School of Engineering and Sciences São Paulo State University (FEC-UNESP), 19274-000, Rosana SP, Brazil. (guilherme.cardim@unesp.br)
[3] Department of Earth Sciences, Faculty of Sciences and Technology, University of Coimbra (UC), 3030-790, Coimbra, Portugal. (ppina@dct.uc.pt)

Keywords: Inpainting, roads, mathematical morphology, digital image processing, remote sensing images.

Abstract

Based on the comparison of three established inpainting techniques, namely Criminisi, Beltamio, and Galerne and Leclaire, our study aimed to identify the most effective method for road restoration after extraction and detection using a Mathematical Morphology operators combined with hybrid techniques of digital image processing in remote sensing images. While all techniques were evaluated based on both visual analysis and quantitative metrics, the Criminisi approach emerged as the better choice. Despite introducing some additional noise, this technique demonstrated superior performance in terms of Completeness and overall Quality, achieving approximately 95.23% and 94.56%, respectively. Its ability to accurately reconstruct linear geometries while effectively removing existing noise highlighted its suitability for road restoration tasks.

1. Introduction

Image processing and computer vision rely on the comparison of techniques to assess their effectiveness in solving specific problems. Comparative analysis of inpainting techniques, specifically for roads, enables the identification of methods that yield accurate and realistic results, taking into account factors such as image quality, urban area complexity, and the nature of the target to be restored.

The restoration of damaged or defective regions in images poses a significant challenge due to information loss within these areas. Existing methodologies to tackle this challenge are commonly categorized into two groups: traditional methods and deep learning methods.

Recent advancements in deep learning-based approaches have showcased their superiority over conventional inpainting algorithms across various scenarios. Deep learning models, particularly those leveraging convolutional neural networks (CNNs), have demonstrated remarkable performance in generating realistic image restorations. Encodings passed through generative models to infer missing content, as described by Dong et al. (2019) and Kuznetsov and Gashniov (2020), have facilitated substantial improvements in restoration accuracy. Furthermore, Esfandiari et al. (2021) have underscored the superior performance of CNN-based methods over conventional approaches, achieving shorter inference times and effectively handling irregular hole patterns. However, it is noteworthy that deep learning-based methods often entail higher computational costs. For instance, the PConv model may demand approximately 60 hours of training (Esfandiari et al., 2021). Nevertheless, deep learning models offer advantages in terms of precision, generalization capabilities, and their ability to address complex image artifacts and extensive damage.

Although advanced, deep learning-based inpainting methods, traditional techniques still harbor advantages in specific scenarios. Traditional methods may exhibit greater speed and require fewer computational resources, particularly advantageous in situations where processing speed is critical or hardware resources are limited. Additionally, traditional algorithms typically afford a clearer understanding of the pixel-filling process, a fundamental aspect in scenarios requiring interpretability. Another advantage lies in their lower data requirements, rendering them suitable for scenarios with sparse labeled data or high labeling costs. Lastly, traditional methods enable greater manual control in the pixel-filling process, beneficial in creative applications necessitating direct intervention in the outcome.

This article focuses on comparing three well-established inpainting techniques widely discussed in the literature. The first technique, developed by Criminisi, Pérez, and Toyama (2004), is based on the principle of filling in missing regions or removing unwanted objects from an image. The second technique, proposed by Beltamio et al. (2000), employs partial differential equations to propagate pixels and fill the gaps in the image. Lastly, Galerne and Leclaire (2017) introduce a technique that utilizes statistical modeling of image texture through a Gaussian scale mixture model, capturing both local and global texture properties.

The main objective of this study is to compare the performance of these three painting techniques when applied to two roads. The analysis covers statistical evaluation with the metrics completeness, correctness, quality, Structural Similarity Index Method (SSIM), and Peak Signal-to-Noise Ratio (PSNR), to infer the quality of the painting results, and visual evaluation to assess their visual results.

This comparative analysis will provide valuable insights into the effectiveness and suitability of different inpainting techniques for roads. The findings will contribute to advancing the field of image processing and assist researchers and practitioners in selecting the most suitable technique for inpainting urban images.

https://doi.org/10.5194/isprs-annals-X-3-2024-245-2024

Although there are inpainting techniques and new methods will continue to emerge, alongside other segmentation methods utilizing deep learning and/or other digital image processing techniques, it is valid that, in the context of road scenes, these three methodologies have not yet been compared. These methodologies were foundational at the time of their implementation and thus remain relevant for this study.

2. Materials and methods

Commercial images from QUICKBIRD, made available for free by the research group, dated July 5th, 2019, were used and captured in the region of Presidente Prudente, State of São Paulo (Figures 3 and 4). The panchromatic band was utilized due to its high spatial resolution (30 cm). In this study, only two targets were considered, deemed complex due to their shape. Circular objects are particularly challenging in inpainting techniques. While it is desirable to evaluate multiple targets for a comprehensive understanding of technique performance, the complexity of the selected targets allowed for a significant and focused comparison among the studied techniques. It employed the Matlab R2018b software for analysis and evaluated the metrics of Completeness, Correctness, and Quality, which are available in the Cartomorph software. Additionally, two other metrics implemented in Matlab R2018b, namely SSIM and PSNR, were utilized.

Below, in Figure 1, the flowchart of the proposed methodology in this work is presented. It is worth noting that the objective is to compare which of the inpainting techniques yields better statistical and visual results, considering that they originate from the same process of detection and extraction (Mathematical Morphology). With this in mind, three distinct inpainting techniques are applied to reconstruct the discontinuous parts of the result obtained from the detection and extraction using mathematical morphology.

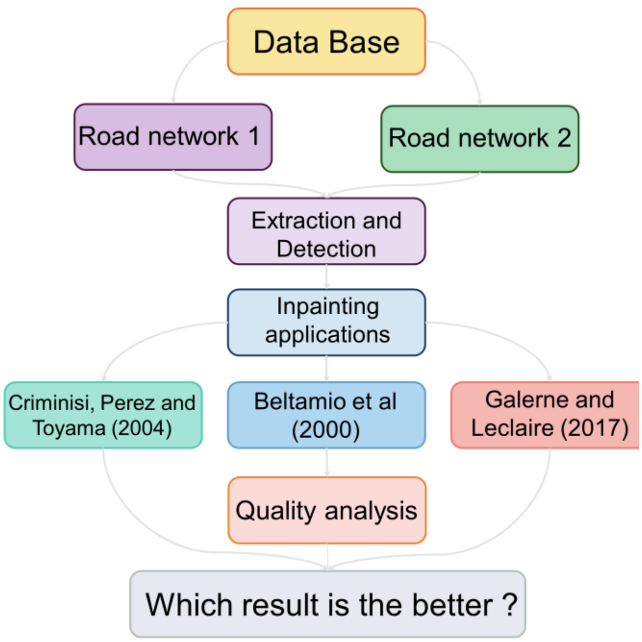

Figure 1. Flowchart

In the flowchart shown in Figure 1, the sequence followed in this work is observed, prioritizing the search for two high-complexity roads. The process of extraction and detection of these objects was carried out, and each one was subjected to an inpainting technique. As a result, a statistical analysis was conducted to determine the best technique for each target, as well as a visual analysis. Subsequently, the question of which result, both statistically and visually, is the better will be answered.

Below, we have the location map of the study area. The two selected roads are located within the municipality of Presidente Prudente, São Paulo, as visible in Figure 2.

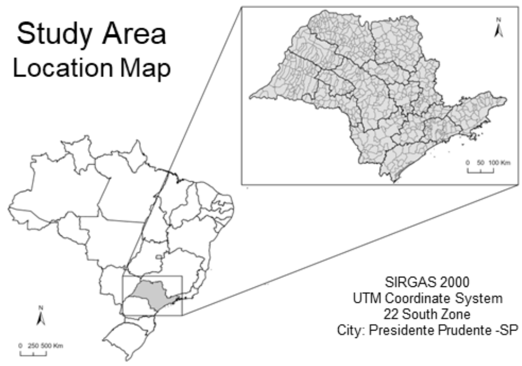

Figure 2. Study Area Location Map of Presidente Prudente.

Additionally, in Figures 3 and 4, you can see the chosen high-complexity targets for this study.

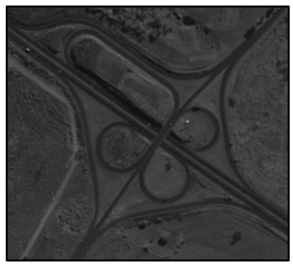

Figure 3. Road networks 1. Region of Presidente Prudente, State of São Paulo

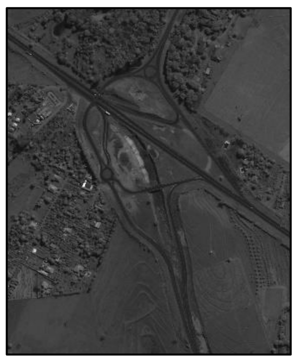

Figure 4. Road networks 2. Region of Presidente Prudente, State of São Paulo

2.1 Extraction and Detection of the Road

The extraction and detection of the target of interest were performed using Mathematical Morphology (MM) operators and thresholding, combined with hybrid techniques of digital image processing (Nascimento et al., 2023). The sequence of operations occurred in pre-processing stages, which were sufficiently necessary to enhance the feature of interest. In the processing stage, the ROI - Region of Interest function was used, which served as a separator of what is the target and what is not. Then, morphological operators were applied to detect the target. Next, non-morphological operators were used to extract the features of interest and evaluate the quality of the results. To evaluate which inpainting technique presented a better performance in the study area, there needed to be discontinuities in the detection so that the post-processing step (inpainting techniques) could improve the quality of the extractions, aiming at the reconstruction of partially detected objects.

2.2 Criminisi, Pérez and Toyama (2004) Inpainting

This Inpainting technique is exemplar-based and is used when you want to reconstruct a region and perform and fill a damaged area with exemplars contained in its neighborhood. To do this a region of the image that is damaged is selected and the processes of reconstruction of regions that have abrupt color change and propagation of texture windows to the other regions is performed iteratively. This algorithm is composed by two main terms, as show Equation 1.

$$P(p) = C(p) * D(p) \tag{1}$$

Where P(p) is the priority term, C(p) is the confidence term and D(p) is the data term. The P(p) defines the pixel of the center patch that has priority to be filled and can be calculated using the confidence term, which describes the texture synthesis, and the data term, which describe the geometric information in the patch. Lastly, the algorithm performs iteratively propagating the geometric information and texture information until the mask region is completed by exemplars using the Sum Squared Error (SSD) as a similarity measure.

2.3 Beltamio et. al. (2000) Inpainting

The Inpainting technique proposed by Bertalmio et al. (2000) is of the Diffusion-Based type and is used to smooth the image and reduce noise iteratively. The process begins by defining an original image and an initial filter, and diffusion is applied to the filtered image so that they are smoothed over time. The diffusion equation is formulated so that regions of higher intensity are preserved, while regions of lower intensity are smoothed. This algorithm uses a non-linear partial differential equation approach to simulate the painters when they restore the museum paintings. This technique can be expressed by a main equation, as shown the Equation 2.

$$I^{(n+1)} = I^n(i,j) + \Delta t I_t^n(i,j), \forall\, (i,j) \in \Omega \tag{2}$$

Where the $I^n(i,j)$ is the input image, n is the number of iteration, Δt is the rate of improvement, $I_t^n(i,j)$ is an update of image I, and Ω is a region of image to be inpainted and represented by the mask. In this approach, Bertalmio et al. (2000) proposed the use of anisotropic diffusion to define the direction field correctly and prevent the lines from crossing, generating the smoothing effect in the inpainted image. Finally, this algorithm performs iteratively and stops when the reaches a maximum iteration number or a threshold, set by the user.

2.4 Galerne and Leclaire (2017) Inpainting

The Galerne and Leclaire (2017) Inpainting technique is based on the use of a mathematical model of image restoration that considers the interaction between adjacent pixels. The method uses partial differential equation transfer equations to calculate the flow of information between pixels and fill in missing or damaged areas in the image. The transfer equation is then applied to the original image to calculate the information flow of neighbouring pixels and texture synthesis.

This inpainting technique use Gaussian Conditional Simulations and we can divide in three steps: estimate a Gaussian texture model to mask region to be inpainted, Sample Gaussian texture model using values on the outer border of the mask and solve a large conditioned linear system. Finally, Galerne and Leclaire (2017) proposed solve this linear system using the Conjugate Gradient Descent from an implementation based on Fast Fourier Transform (FFT).

2.5 Statistical Analysis of cartographic extractions

It is crucial to assess the reliability of the obtained results by evaluating them using appropriate metrics. In this study, the evaluation of inpainting techniques will be performed using the Cartomorph software developed by Cardim (2015). This software provides a range of metrics that can be used to compare the inpainting images with a reference image. The metrics used in this work will be the conventional ones: Completeness (Com), Correctness (Cor), and Quality (Qua).

Apart from Cartomorph, two more metrics, SSIM (Structural Similarity Index Method) and PSNR (Peak Signal-to-Noise Ratio), implemented using Matlab R2018b, will be used. SSIM assesses the structural similarity between the reference image and the inpainting image, providing information on the quality of the resulting inpainting image. Similarly, PSNR calculates the level of noise introduced during the inpainting process by comparing the signal-to-noise ratio of the inpainting image with that of the reference image.

Next in Table 1, we present the metrics used in this study: completeness, correctness, quality, SSIM, and PSNR. These metrics serve as quantitative measures to evaluate the performance and quality of the inpainting techniques employed.

Com	$\frac{TP}{TP+FN}$	(3)
$Corr$	$\frac{TP}{TP+FP}$	(4)
Qua	$\frac{TP}{TP+FP+FN}$	(5)
SSIM	$\frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$	(6)
PSNR	$20\log_{10}\left(\frac{\mathrm{MAX_f}}{\sqrt{\mathrm{MSE}}}\right)$ MSE $= \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\lVert f(i,j) - g(i,j)\rVert^2$	(7)

Table 1. Evaluation Metrics.

The first metric is completeness (Com) and is calculated using Equation 3. It reflects how many pixels the approach detected correctly from the ground-truth image or reference mask. The metric ranges from 0 to 1, with 1 being the ideal value. TP stands for true positives, which means pixels correctly identified by the approach. Meanwhile, FN represents the false negatives or the pixels the approach missed according to the ground truth.

The correctness (Corr) metric, defined in Equation 4, shows the percentage of correctly identified pixels by the method compared to the ground truth (GT). An ideal score of 1 indicates that all

https://doi.org/10.5194/isprs-annals-X-3-2024-245-2024 | © Author(s) 2024. CC BY 4.0 License.

interest pixels are correctly identified. FP stands for false positives, which identifies falsely detected pixels.

The third measure is the "quality" (Qua) from Equation 5. It considers the previous two measures to give an overall performance indication. Ideally, Qua equals 1, the highest level of quality, representing exceptional performance. Qua can be used to describe the achieved quality and provide a measure of the approach's overall performance.

The SSIM evaluation metric compares the inpainted image x with the reference image y and provides values ranging from -1 (perfect anti-correlation) to 1 (perfect correlation). This metric uses the mean, variance, and covariance, as show Equation 6, and two constants C1 and C2. The SSIM is robust to changes in brightness and contrast, enabling it to measure of images reliably and accurately.

The PSNR, defined by Equation 7, compares the inpainted image $f(i,j)$ with reference image $g(i,j)$, using the maximum signal value $\mathrm{MAX_f}$ of inpainted image and the Mean Squared Error (MSE) between $f(i,j)$ and $g(i,j)$.

3. Results and discussion

The results of this study were satisfactory, as can be seen in Figure 5 (d-f), where the inpainting techniques were applied to the selected road. The reconstruction was clear and visible (highlighted in green). In Figure (b), detection and extraction were performed using mathematical morphology and digital image processing techniques, and (c) was used as a reference to perform the evaluation metrics. In Figure (d), the technique (Criminisi, Pérez, and Toyama, 2004) was applied, which was necessary for the reconstruction of the partially detected linear geometries but introduced noise during the process of repairing curved features. In Figure (e), the technique (Bertalmio, 2000) was applied, and it was observed that the damaged area was not reconstructed and generated a blurring effect in the inpainted areas. In Figure (f), the technique (Galerne and Leclaire, 2017) was used, and it was able to correctly reconstruct small regions, but circular regions introduced noise.

To support the visual analysis, Table 2 reveals that Criminisi et al.'s (2004) technique achieved higher values in terms of Completeness and SSIM, approximately 95.23% and 94.56%,

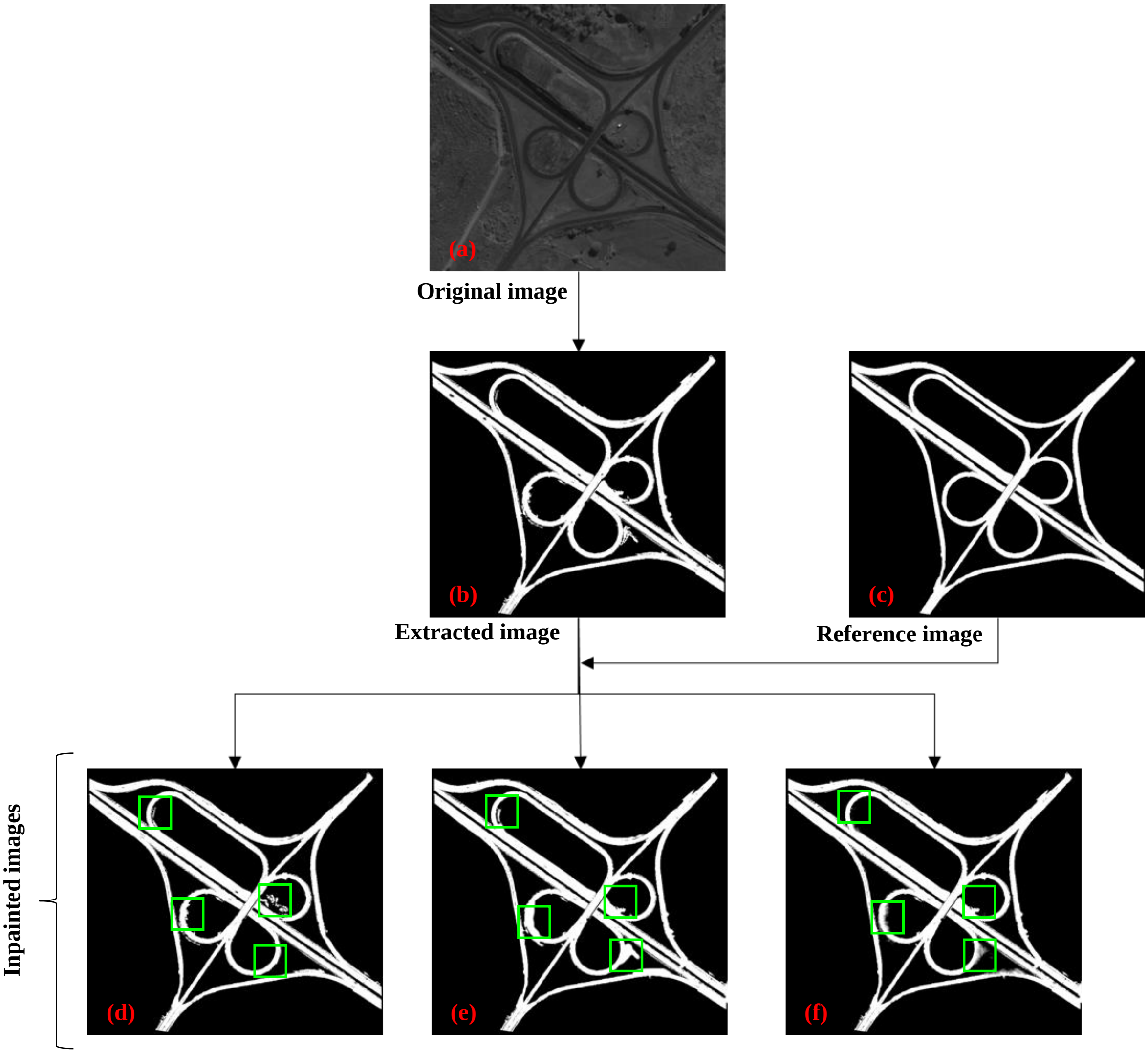

Figure 5. Process and result of applying the extracted image to the Inpainting techniques (Target 1). (a) Original Image with the road network. (b) Extracted image by Mathematical Morphology and Thresholding. (c) Reference image to perform in evaluation metrics. (d) Inpainted image by Criminisi, Pérez and Toyama (2004) technique. (e) Inpainted image by Bertalmio et al. (2008) technique. (f) Inpainted image by Galerne and LeClaire (2017) technique.

respectively. Bertalmio et al. (2000) presented higher Quality values, around 82.08%, while Galerne and Leclaire (2017) obtained a higher Quality value of 77.78%. Considering that Quality is a combination of Correctness and Completeness, it is evident that the other techniques achieved a higher value in one metric but a lower value in the other, resulting in a lower Quality compared to Galerne and Leclaire (2017). Galerne and Leclaire (2017) also achieved the same SSIM value as Criminisi et al.'s 2004 technique and a higher PSNR value of approximately 18.96%.

Feature 1	Extracted image (MM and DPI)	Criminisi et al. (2004)	Bertalmio et. al., (2000)	Galerne and Leclaire, 2017
Completeness (%)	82.15	**95.23**	92.72	93.78
Correctness (%)	99.39	79.37	**82.08**	81,88
Quality (%)	81.32	76.43	77.23	**77.78**
SSIM (%)	94.57	**94.56**	94.45	**94.56**
PSNR (dB)	18.38	18.78	17.89	**18.96**

Table 2. Evaluation Metrics: Target 1.

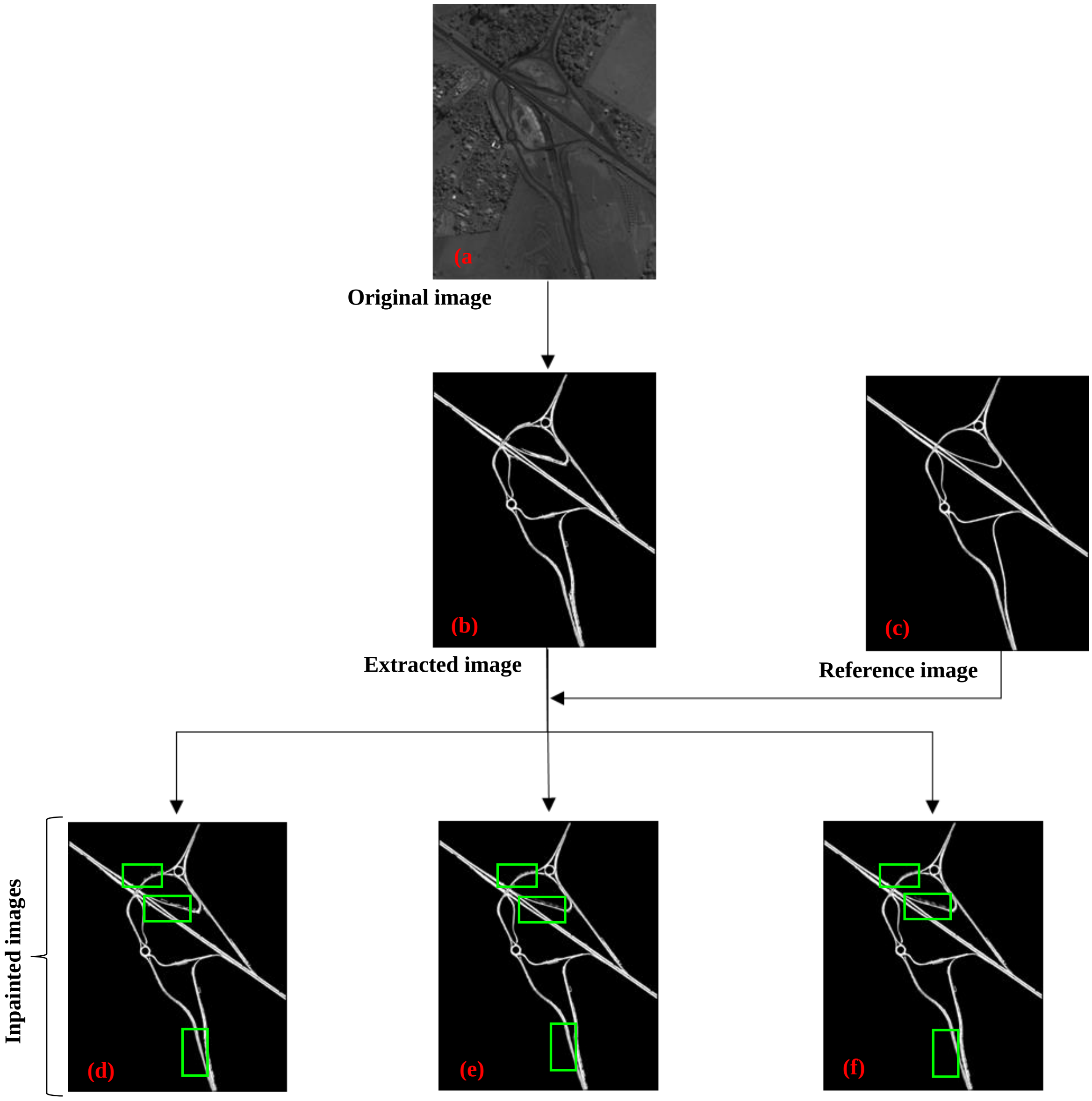

Figure 6. Process and result of applying the extracted image to the Inpainting techniques (Target 2). (a) Original Image with the road network. (b) Extracted image by Mathematical Morphology and Thresholding. (c) Reference image to perform in evaluation metrics. (d) Inpainted image by Criminisi, Pérez and Toyama (2004) technique. (e) Inpainted image by Bertalmio et al. (2008) technique. (f) Inpainted image by Galerne and LeClaire (2017) technique.

For Figure 6, a similar pattern was observed in the obtained results. In the original Figure (a), the image obtained through mathematical morphology (b), and the reference Figure (c), specific characteristics of the study area can be observed. Analyzing the results of the inpainting techniques, we have d) The Criminisi, Pérez, and Toyama (2004) technique introduced some additional noise that was not present in the originally extracted image. However, it also managed to remove some of the existing noise. e) The Bertalmio et al. (2008) technique proved effective in removing some noise, but like in the other images, it introduced noise in a specific region of the image. f) With the Galerne and Leclair (2017) technique, there is noticeable image smoothing, with visible blurriness. Blurring artifacts resembling motion blur, which were not originally present, can be observed despite the noise reduction.

To complement the visual analysis, the results in Table 3 were considered. This table found that the Criminisi, Pérez, and Toyama (2004) technique achieved higher values in Completeness and Quality, approximately 95.23% and 94.56%, respectively. Meanwhile, Bertalmio et al. (2000) obtained a higher value of correctness, 82.08%. Galerne and LeClair (2017) presented a lower Quality value compared to the other techniques, without showing higher values for any of the metrics. These findings emphasize the importance of selecting inpainting techniques that prioritize preserving the shape and delineating the elements to be reconstructed.

Feature 2	Extracted image (MM and DPI)	Criminisi et al. (2004)	Bertalmio et. al., (2000)	Galerne and Leclaire, 2017
Completeness (%)	82.15	**95.23**	92.72	93.78
Correctness (%)	99.39	79.37	**82.08**	81.88
Quality (%)	81.32	**94.56**	77.23	77.78
SSIM (%)	**98.15**	97.44	98.12	98.11
PSNR (dB)	21.82	22.63	**23.22**	23.16

Table 3. Evaluation Metrics: Target 2.

4. Conclusion

In this paper, we evaluated various inpainting techniques for a road network. The findings, as shown in Figure 5 (d-f), yielded satisfactory results using the tested techniques. It's worth noting that each approach had advantages and disadvantages. The Criminisi, Pérez, and Toyama (2004) technique, demonstrated in Figure (d), was successful in reconstructing linear geometries but introduced noise in curved features. On the other hand, the Bertalmio (2000) technique, applied in Figure (e), resulted in blurring and failed to fully reconstruct the damaged area. The Galerne and Leclaire (2017) technique, utilized in Figure (f), effectively fixed small regions but introduced noise in circular areas.

To support the visual analysis, we referred to Table 2. The metrics of Completeness and SSIM indicated higher values for the Criminisi et al.'s (2004) technique, at approximately 95.23% and 94.56%, respectively. The Bertalmio et al.'s (2000) method demonstrated better Quality, with a score of around 82.08%, while Galerne and Leclaire (2017) achieved a higher Quality of 77.78%. It is worth noting that Quality is correlated with Correctness and Completeness. Therefore, despite the other techniques excelling in one metric, Galerne and Leclaire (2017) had an overall higher Quality. Additionally, their SSIM value matched that of the Criminisi et al. (2004) technique, coupled with a higher PSNR value of approximately 18.96%.

The results obtained from Figure 6 exhibited similar patterns and confirmed the characteristics and limitations of each technique. The Criminisi, Pérez, and Toyama (2004) technique introduced some noise but also reduced existing noise. The Bertalmio et al. (2008) technique successfully removed some noise but introduced noise in a specific area. The Galerne and Leclair (2017) technique noticeably smoothed the image, resulting in visible blurriness and motion blur-like artifacts. Table 3 further supported these findings, where the Criminisi, Pérez, and Toyama (2004) technique achieved higher values in Completeness and Quality (around 95.23% and 94.56%, respectively), while Bertalmio et al. (2000) obtained a higher value in Correctness (82.08%). Galerne and LeClair (2017) performed worse than the other techniques in terms of Quality without surpassing them in any of the metrics.

Based on the combined visual analysis and quantitative metrics provided, the Criminisi, Pérez, and Toyama (2004) technique emerges as the most effective inpainting method among the evaluated options. Despite introducing some additional noise, this technique demonstrates superior performance in terms of Completeness and overall Quality, achieving approximately 95.23% and 94.56%, respectively. Its ability to accurately reconstruct linear geometries while effectively removing existing noise highlights its suitability for road restoration tasks. While other techniques exhibit strengths in specific metrics, such as Bertalmio et al. (2000) excelling in Correctness and Galerne and Leclaire (2017) displaying higher SSIM and PSNR values, neither surpasses the comprehensive performance of the Criminisi, Pérez, and Toyama (2004) approach.

In addition, Bertalmio et al. (2000) and Galerne and Leclaire (2017) techniques a certain amount of blurring in the regions where the inpainting was applied. Thus, for road networtk inpainting scenarios where both shape preservation and noise reduction are paramount, the Criminisi, Pérez, and Toyama (2004) technique stands out as the better choice.

In conclusion, this study emphasizes the significance of selecting inpainting techniques that prioritize preserving shape and accurately reconstructing elements while minimizing noise and blurring artifacts. Future research could focus on developing hybrid approaches that combine the strengths of different methods to overcome their individual limitations. Even though deep learning can provide more precise results, it has been shown that less resource-intensive approaches can yield acceptable outcomes for complex images. Additionally, to enable a broader evaluation in future studies, including the analysis of more images, not only of high resolution but also of medium resolution, as applied in Nascimento et al. (2023) for CBERS 4 images. Furthermore, incorporating more statistical metrics, as illustrated in Fontoura Júnior et al. (2023), could enhance the robustness of inpainting technique evaluations and contribute to further advancements in the field.

There is a certain complexity in analyzing road networks. Even with high spatial resolution images, the complexity increases due to intersections, curves, and the surrounding areas of the roads. This complexity affects both the extraction and reconstruction processes using inpainting techniques. It is recommended that future research expands the database to compare other algorithms and observe how they perform with different, potentially more complex targets, possibly with lower spatial resolutions.

References

Bertalmio, M. et al. Image inpainting. In: *Proceedings of the 27th annual conference on Computer graphics and interactive techniques*. 2000. p. 417-424. Doi: /10.1145/344779.344972.

Cardim, G. P. Development of the CARTOMORPH computer system to process remote sensing images. *Master Thesis*. 2015.

Criminisi A., perez P., Toyama K. Region filling and object removal by exemplar-based image inpainting. *IEEE. Transactions on Image Processing*, vol. 13, no. 9, pp. 1200-1212, Sept. 2004. Doi: 10.1109/TIP.2004.833105.

Dong, J. Yin, R. Sun, X. Li, Q. Yang, Y., Qin, X. "Inpainting of Remote Sensing SST Images With Deep Convolutional Generative Adversarial Network," in *IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 2, pp. 173-177, Feb. 2019, doi: 10.1109/LGRS.2018.2870880.

Esfandiari, H., Weidert, S., Kövesházi, I., Anglin, C., Street, J., Hodgson, A.J. (2021), Deep learning-based X-ray inpainting for improving spinal 2D-3D registration. *Int J Med Robot*, 17: e2228. https://doi.org/10.1002/rcs.2228.

Fontoura Júnior, C. F. M., Cardim, G. P., Nascimento, E. S., Colnado, M., Casaca, W. C. D. O., da Silva, E. A.: Assessing the effectiveness of inpainting techniques for enhancing feature extraction quality in remote sensing imagery, *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci*., X-1/W1-2023, 65–72, https://doi.org/10.5194/isprs-annals-X-1-W1-2023-65-2023, 2023.

Galerne, B. Leclaire A. An Algorithm for Gaussian Texture Inpainting. *Image Processing Online*, vol. 7, pp. 262--277, 2017. Doi:10.5201/ipol.2017.198.

Horé, A., Ziou, D., Image Quality Metrics: PSNR vs. SSIM. 2010 20th *International Conference on Pattern Recognition, Istanbul, Turkey,* 2010, pp. 2366-2369, doi.org/10.1109/ICPR.2010.579.47p.

Kuznetsov, A., Gashnikov, M. "Remote Sensing Image Inpainting with Generative Adversarial Networks," *2020 8th International Symposium on Digital Forensics and Security (ISDFS),* Beirut, Lebanon, 2020, pp. 1-6, doi: 10.1109/ISDFS49300.2020.9116347.

Mathworks Inc. “Student Edition of MATLAB Version 5 for Windows”. Prentice Hall, Upper Saddle River, New Jersey, 1997.

Nascimento, E. S., Ferreira, A. A. L., Godoy, T. G., Fontoura Júnior, C. F. M., Cardim, G. P., Pina, P., da Silva, E. A.: Cartographic features extraction methodology in remote sensing images aiming at the cartographic update of allotments, *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci*., X-1/W1-2023, 851–856, https://doi.org/10.5194/isprs-annals-X-1-W1-2023-851-2023, 2023.

Nath, Jyotirmoy. Image Inpainting Using Deep Learning. *PhD Thesis*. *CENTRAL INSTITUTE OF TECHNOLOGY*. 2023.