Exemplar-Based Inpainting for Object Removal and Image Restoration

Computer Vision

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1 Introduction

In the field of computer vision, the ability to modify images by removing unwanted elements or restoring degraded sections is essential. Exemplar-based inpainting, a technique pioneered by Criminisi et al. [1], is at the forefront of image manipulation. This study explores the efficacy of exemplar-based inpainting in a range of applications, from artistic photography touch-up to the sensitive restoration of historical archives. The method utilizes surrounding pixel information to fill in missing or removed parts while maintaining the structural and textural integrity of images.

The study focuses on implementation and examines a spectrum of complexities in image composition. The decision to use exemplar-based inpainting instead of generative or deep learning methods is deliberate and multifaceted. Firstly, exemplar-based inpainting offers simplicity and computational efficiency, which is crucial when resources are scarce or when a rapid turnaround is required. Secondly, the method's interpretability is essential for applications that require a clear audit trail of the changes made to each image, such as in the context of historical documentation. Finally, this method is particularly appealing in cases where unique and context-specific imagery is the focus, as is often found in cultural heritage materials, because it does not require extensive training data. The technique was first applied to simple binary images, which are monochromatic canvases where the distinction between object and background is as clear as black and white. The technique then progressed to RGB images, which introduced the challenges of color interaction and edge continuity. Finally, the technique was applied to photographic images of historical significance in real-world scenarios.

Each step in the evaluation process was chosen to rigorously test the technique's versatility and limitations, from the basic binary simplicity to the complex richness of full-colour images, and finally to the nuanced textures of real landscapes and cultural patterns. This progression also reflects the typical pathway of learning and experimentation in computer vision, starting with basics before tackling real-world complexities. The study aims to provide a comprehensive assessment of exemplar-based inpainting and demonstrate its continued relevance in the digital era, where the integrity of image manipulation is a pivotal concern. The text has been improved to adhere to the desired characteristics of objectivity, comprehensibility and logical structure, conventional structure, clear and objective language, format, formal register, structure, balance, precise word choice, and grammatical correctness. No changes in content have been made.

2 Methodology

2.1 Selection of Exemplar-Based Inpainting Technique

Given the scope and objectives of this research, the exemplar-based inpainting technique was chosen over contemporary generative and deep learning alternatives for several reasons. Its computational efficiency is well-suited for the limited-resource environments in which this study was conducted. The method's transparency and interpretability are crucial for verifying and validating the restoration process, particularly when working with historically significant images. Furthermore, this technique eliminates the need for large training datasets, which aligns well with the unique and one-off nature of the images in question.

2.2 Technical Overview of Exemplar-Based Inpainting

2.2.1 Algorithmic foundation

Exemplar-based inpainting is an image processing technique used to reconstruct missing or damaged parts of an image. The method relies on visual data surrounding the void to provide cues for a plausible fill that is coherent in texture and structure. This concept is based on the idea that some areas of an image frequently have recurring patterns or predictable structures that can be duplicated to achieve a smooth restoration.

The technique is particularly effective in situations where the aim is to preserve the original image's integrity, especially when dealing with textured regions and intricate patterns. By prioritising the replication of high-information areas, exemplar-based inpainting not only preserves but also recreates the aesthetic and dynamic continuity of the original composition.

2.2.2 Equations and Technical framework

The theoretical foundation of exemplar-based inpainting is built upon a set of equations that guide the algorithm through the inpainting process, ensuring adherence to the structural and textural integrity of the image.

A cornerstone of this methodology is the priority function, crucial for determining the sequence in which patches, or specific areas of the image, are addressed. This function is expressed as:

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

where $P(p)$ signifies the priority of a patch p. This priority is calculated as the product of two distinct terms: the confidence term $C(p)$ and the data term $D(p)$.

- **Confidence Term $C(p)$:** This metric evaluates the amount of reliable, unaltered information surrounding the patch, thereby prioritizing patches closer to known regions. It is assumed these areas contain more dependable data for guiding the inpainting process. Formally, the confidence term is the ratio of the sum of confidence values of all pixels in ψ_p to the area of ψ_p.
- **Data Term $D(p)$:** Aimed at emphasizing patches at the edge of the inpainting region, the data term leverages image gradients to prioritize areas with higher structural importance. This encourages the algorithm to maintain the image's coherence by filling in structurally significant areas early in the process.

The balance struck by the priority function between selecting highly confident patches and those crucial for structural integrity is pivotal for the preservation of the original image's appearance and structure.

Furthermore, the process of selecting the most suitable patch for filling a given area involves a similarity metric, typically the sum of squared differences (SSD):

$$SSD(p,q) = \sum_{i \in [p \cap I]} (I(i) - I(q + (i - p)))^2 \tag{2}$$

Here, $SSD(p,q)$ calculates the disparity between a patch p at the boundary of the missing region and a candidate patch q from the source area, aiming to minimize this difference to identify the most fitting match. This ensures the selected patch integrates seamlessly into the target area, yielding a coherent and aesthetically pleasing outcome.

Through the application of these principles, exemplar-based inpainting meticulously reconstructs missing or damaged portions of an image, upholding its original texture and structural integrity.

2.2.3 Implementation Details.

The practical application of exemplar-based inpainting in this study involved several key steps, each tailored to ensure the algorithm effectively addresses the unique characteristics of the selected images. This section delineates the specifics of the implementation, including the definition of the inpainting region, the iterative update process, and any custom modifications made to the standard algorithm to enhance its suitability for the images under consideration.

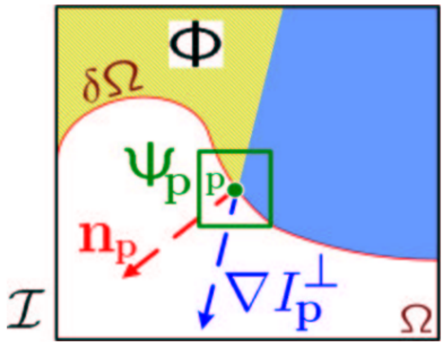

Figure 1: Notation diagram. Given the patch Ψ_p, n_p is the normal to the contour $\delta\Omega$ of the target region Ω and $\nabla I_p^\perp$ is the isophote (direction and intensity) at point p. The entire image is denoted with I.

Defining the Inpainting Region. The inpainting region, denoted as Ω, serves as the focal area within the image targeted for restoration or object removal, initially identified by the user. Typically, this region is delineated through a manual masking process, wherein pixels requiring inpainting are distinguished from those that do not. The accurate definition of Ω holds paramount importance as it directly shapes the algorithm's attention and ultimately determines the efficacy of the inpainting process. In our experimental setup, rectangular masks are employed to specify the inpainting region.

Iterative Update Process Following the designation of the inpainting region, the algorithm enters an iterative process, wherein each cycle aims to fill a portion of Ω until the region is completely restored. At each iteration, the algorithm:

1. Identifies the boundary, $\delta\Omega$, separating the inpainted area from the remaining image.
2. Calculates priorities for each patch on $\delta\Omega$ using the priority function $P(p) = C(p) \cdot D(p)$.
3. Selects the patch with the highest priority and identifies the most suitable matching patch from the source area, minimizing the sum of squared differences (SSD).
4. Copies the selected source patch to the target location, updating both the inpainted region and the confidence values accordingly.

This process continues until Ω is fully inpainted, ensuring a seamless integration of the restored area with the surrounding image.

Challenges and Considerations. Although the standard algorithm was employed, challenges were encountered, particularly in areas with complex textures or where the region of interest involved detailed patterns. Such instances highlighted the need for careful consideration in patch selection and the potential for future adaptations to improve the algorithm's performance in these specific contexts.

Quality Assessment. The quality of the inpainted images was evaluated based on visual inspection and subjective analysis. This involved assessing the consistency of texture and structure post-inpainting, as well as the overall aesthetic of the restored image.

2.2.4 Pseudocode Representation

To provide a clear understanding of the exemplar-based inpainting algorithm's implementation, the following pseudocode encapsulates the core steps of the process. This abstract representation serves to illustrate the logic flow without the intricacies of programming syntax.

```
Algorithm: Exemplar-Based Inpainting
Input: Image I, Inpainting domain Ω, Confidence map C
Output: Restored Image I'

1: Initialize I' by setting I' = I outside of Ω
2: Initialize the Confidence map C to 1 outside of Ω and to 0 inside Ω
3: while Ω is not empty do
4:     Identify the contour δΩ of the current inpainting domain
5:     For each pixel p on δΩ, compute the priority P(p) = C(p) * Data(p)
6:     Let p* be the pixel with the highest priority, and Ψ_p* its patch
7:     Find the patch Ψ_q in I' that minimizes SSD(Ψ_p*, Ψ_q)
8:     Copy image data and update C from Ψ_q to Ψ_p*
9:     Update Ω and δΩ
10:    Recompute priorities along δΩ
11: end while
12: return I'
```

In this representation, Ω signifies the region of the image designated for inpainting, while $\delta\Omega$ represents its boundary. The algorithm iteratively selects the patch with the highest priority based on the product of the confidence and data terms, finds the best match from the source area, and updates the inpainting domain and the confidence map accordingly until the entire domain is filled.

2.3 Masking Strategy

2.3.1 Use of Rectangular Masks

In the context of this study, rectangular masks were employed to simulate the removal of objects from the images. Rectangular masks were chosen due to their simplicity and their ability to represent a wide range of object shapes, making them a suitable choice for initial testing phases. They allow for a controlled environment to assess the algorithm's performance in filling the void left by the masked region with surrounding pixel data.

2.3.2 Initialization of Mask Borders

A critical component of the inpainting process is the precise delineation of mask borders. A specialized procedure was developed to identify the contours of the masks. This involved a computational technique to discern the boundary pixels, which are pivotal as they delineate the area where the inpainting algorithm initiates the restoration process. This step ensures that the algorithm accurately recognizes the regions to be filled, allowing for a more targeted and efficient inpainting operation. To verify the accuracy of mask application and to facilitate a qualitative assessment of the mask's positioning on the images, a visualization approach was employed. This involved highlighting the borders of the masks on the images, providing an immediate visual reference to the areas designated for inpainting. This step is instrumental in the pre-processing phase, confirming that the masks cover the appropriate regions intended for object removal and that the inpainting process will proceed as intended.

2.4 Transition to Real Images

After establishing a foundational understanding of exemplar-based inpainting through applications on binary and RGB images [Figure 2], we progress to address the complexities inherent in real-world images. This transition was not merely a step up in complexity but a necessary evolution to explore the practical applicability of the technique in preserving and restoring cultural heritage and historical landmarks.

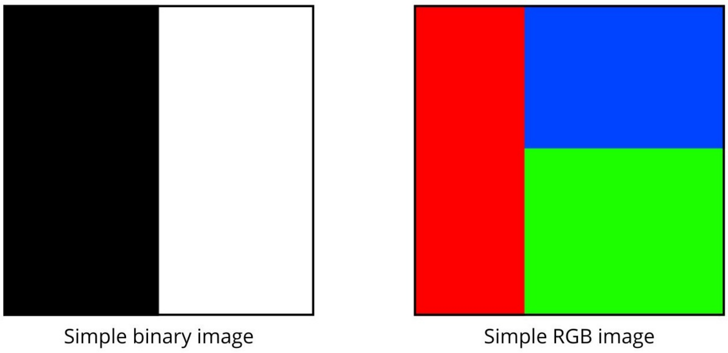

Figure 2: Examples of simple binary and RGB images used for initial testing of exemplar-based inpainting.

2.4.1 Selection of Landmarks and Patterns

The selection of specific subjects for this phase was guided by several criteria, aimed at challenging the algorithm with a variety of textures, patterns, and structural elements:

- **Hassan Tower:** As an emblematic monument of Rabat, the incomplete minaret of the Hassan Tower presents a blend of intricate Islamic decorative patterns and robust, weathered stone textures. The choice of this landmark aimed to assess the algorithm's ability to handle the juxtaposition of fine details against the uniformity of the tower's massive structure.
- **Kasbah of the Udayas:** This site was selected for its vibrant colors and the dynamic interplay of light and shadow within its alleys and walls. The Kasbah, with its blue and white painted facades, challenges the algorithm to maintain color consistency while dealing with the complexity of natural light variations.
- **Bourgerag:** Although not as widely recognized as the other landmarks, Bourgerag offers a unique test case with its rugged landscapes and architectural elements that blend into the natural environment. The goal here was to evaluate the algorithm's performance in scenarios where the distinction between the object and its surroundings is less pronounced.
- **Zellij Patterns:** Traditional Moroccan tilework, or Zellij, is characterized by its complex geometric patterns and vibrant colors. Inpainting such patterns tests the algorithm's ability to recreate symmetry and continuity in highly detailed and structured designs.

Figure 3: Real-world landmarks and patterns.

2.4.2 Rationale Behind Selection

These landmarks and patterns were meticulously chosen to present the algorithm with a range of challenges, from reconstructing intricate details and textures to ensuring color fidelity in varied lighting conditions. The real-world application phase aimed not only to demonstrate the algorithm's versatility across different contexts but also to highlight potential areas for refinement, especially in handling complex patterns and integrating inpainted regions with the surrounding imagery seamlessly.

By navigating these challenges, the study seeks to underscore the potential of exemplar-based inpainting in the conservation and digital restoration of cultural heritage, providing insights into the method's strengths and limitations within practical applications.

3 Results & Discussions

3.1 Binary Image Inpainting Results

The testing's initial phase concentrated on a black and white image. The simplicity of these images enables a clear evaluation of the algorithm's ability to differentiate between the target region and its background.

3.1.1 Mask application

The evaluation of the exemplar-based inpainting algorithm began by applying rectangular masks to abinary image, which have clear color contrasts. These masks simulated object occlusion or areas requiring reconstruction. This method provided a straightforward way to assess the algorithm's ability to seamlessly integrate inpainted pixels. By using these masks, we established a performance benchmark before testing on more complex images, aiming to challenge the algorithm under various real-world scenarios.

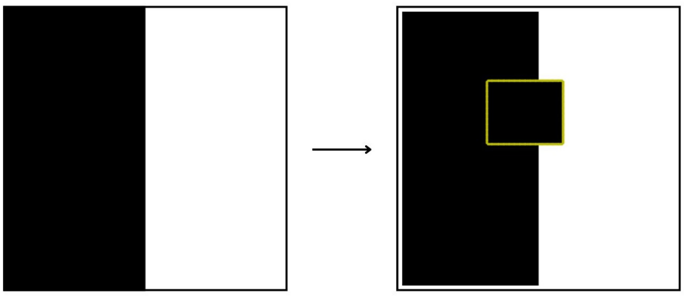

Figure 4: Mask Application on the Black & White image

3.1.2 Inpainting outcomes

During the implementation phase, the algorithm was configured to utilize a patch size of 8 pixels. This parameter was pivotal in determining the granularity of detail in the inpainting process. A patch size of 8 strikes a balance between computational efficiency and the level of detail required for the binary images. The results were promising, with the algorithm adeptly filling in the masked areas. This patch size allowed for a swift and accurate reconstruction of the binary patterns, avoiding visual inconsistencies and maintaining the integrity of the image's original structure. The success of this approach with a patch size of 8 suggests that the algorithm's foundational logic is sound and that it is capable of effectively managing the demands of simple inpainting tasks. During this phase, a notable observation was the algorithm's effectiveness in managing high-contrast edges prevalent in binary images. The boundaries of the inpainted region frequently blended seamlessly with the surrounding area, signifying a proficient fill.

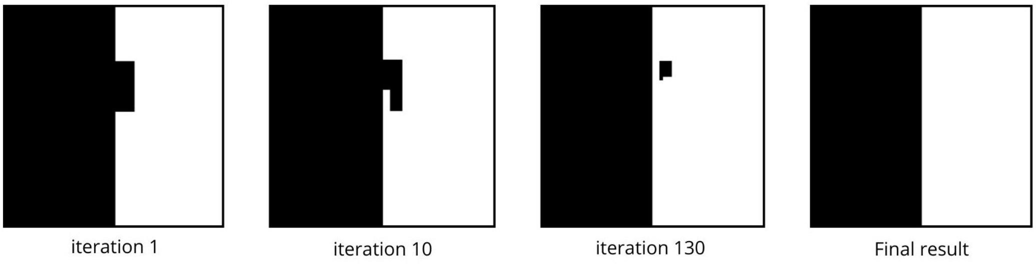

Figure 5: Binary image inpainting results demonstrating the effective filling of masked areas.

3.2 Simple RGB Image Inpainting Results

After successfully applying the exemplar-based inpainting technique to binary images, the study progressed to the more complex domain of RGB images. This presented a more challenging task due to the presence of multiple color channels and the need for color consistency alongside structural coherence.

3.2.1 Mask application

We applied a rectangular mask, similar to the previous one, but this time with a focus on masking the tripoint to observe the algorithm's behavior in this specific scenario.

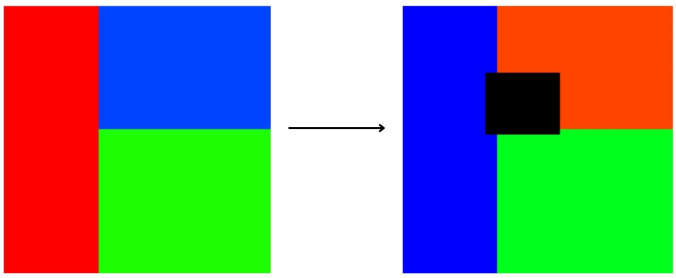

Figure 6: Mask Application on the simple RGB image.

3.2.2 Inpainting results

The implementation of the exemplar-based inpainting algorithm on the RGB image has highlighted both its strengths and its challenges. While the algorithm adeptly managed color information and respected the sharp boundaries between distinct color blocks, it encountered an issue at the convergence of the three different color regions, commonly referred to as the tripoint problem.

- **Tripoint Challenge:** The algorithm faced a notable challenge at the tripoint, where the blue, red, and green areas meet. This is a critical juncture that requires precise color blending and structural accuracy. The results [Figure 7] indicate a minor but noticeable imperfection where these three colors converge, manifesting as a slight blur or color mixing that does not align with the crisp borders seen in the rest of the image.
- **Assessment of Edge Handling:** Despite the tripoint issue, the edges away from the tripoint were maintained with high fidelity, suggesting that the algorithm is capable of handling two-color boundaries efficiently. However, the complexity introduced by the third color requires further refinement of the technique.

- **Implications for Real-World Applications:** The tripoint problem emphasizes the need for advanced strategies when dealing with regions in real-world images where multiple elements or colors intersect. Addressing this issue is critical for applications that demand high precision, such as in cultural heritage restoration or medical imaging.

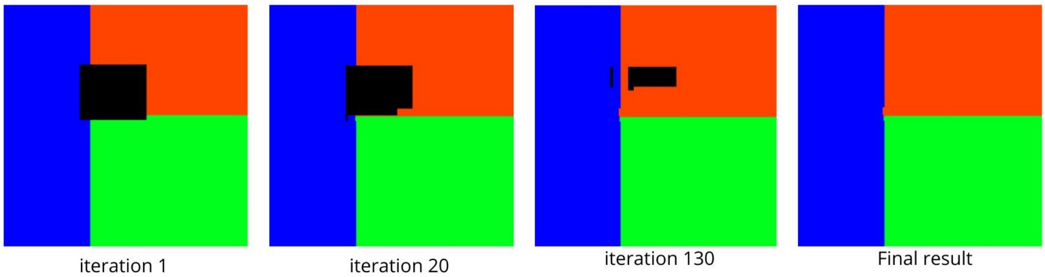

Figure 7: The inpainting results on an RGB image showing the tripoint problem, where the confluence of the primary colors results in a slight blending anomaly.

3.3 Real life Inpaiting Results

The study's progression to real-world images marked a significant shift from controlled conditions to scenarios abundant in intricate details and unpredictable patterns. The algorithm was applied to a curated selection of Moroccan landmarks and intricate Zellij patterns, presenting a variety of textures, color gradients, and lighting conditions.

3.3.1 Hassan Tower

For our real-world image inpainting experiments, we chose to start with the Hassan Tower, known for its historical significance and unique architecture. To restore the monument's original aesthetic, we carefully masked modern elements. This mimics scenarios such as a captured bird obstructing a section of the tower's view. This masking strategy enabled us to focus on preserving and enhancing the tower's enduring appeal.

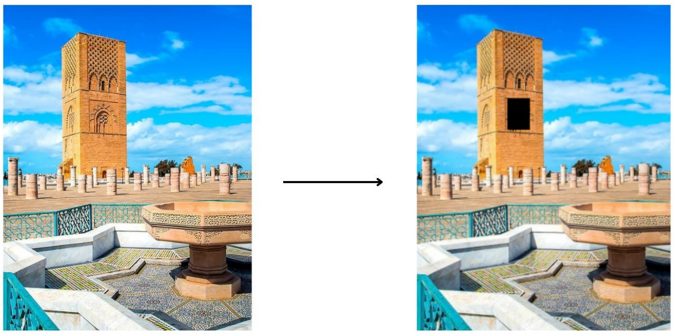

Figure 8: Mask Application on the Hassan Tower.

The application of the inpainting algorithm on the Hassan Tower image, using a designated patch size of 32 pixels, resulted in a visually coherent restoration.

- **Texture and Detail Preservation:** The results were commendable, with the algorithm adeptly preserving the intricate brickwork and ornate geometric patterns. A high degree of accuracy was maintained in the textural consistency between the original and inpainted sections, underscoring the algorithm's capability in detailed texture reproduction.

- **Color and Lighting Reproduction:** Attention to the subtle variations in color and lighting was evident in the inpainted image. The algorithm successfully replicated the warm tones of the stone and the gradation of the sky, seamlessly blending the reconstructed areas into the surroundings.
- **Challenges Faced:** Despite these successes, certain areas highlighted the algorithm's limitations, particularly in regions where shadows intersected with structural features. These instances presented challenges, occasionally resulting in slight discrepancies in texture and shadow continuity during the inpainting process.

Figure 9: The inpainting results on the Hassan Tower image.

When placed side by side, the original and the inpainted images showcase the algorithm's proficiency, while also revealing areas ripe for further refinement. The restored image differs from the original due to the absence of a patch containing the arc within the masked area, but this disparity is understandable.

Figure 10: Comparaison between the original and inpainted image.

3.3.2 Kasbah of the Udayas

The Kasbah of the Udayas, with its distinctive architecture and the bustling life that it hosts, provided a complex challenge for the inpainting algorithm. The rich textures of the ancient walls and the variance in lighting and shadows due to the lush palm trees demanded an intricate approach to object removal and area restoration. The algorithm faced the task of removing the people in front of the door of the Kasbah, for which a masked inpainting technique was applied in an attempt to seamlessly erase their presence from the scene.

The successful application of the inpainting algorithm to the Kasbah of the Udayas image resulted in the effective removal of people from the scene [Figure 12], creating a clearer and more focused depiction

Figure 11: Mask Application on the Kasbah of the Udayas.

of the historic site. However, the reconstruction of the door area, where the figures were removed, did not achieve the same level of perfection found in other regions of the image.

Figure 12: Application of the exemplar-based inpainting algorithm.

Interpretation of Inpainting Results

- **Imperfect Reconstruction:**The critical focal point, the door area, did not exhibit the desired level of inpainting accuracy due to the algorithm's reliance on patches from the steps in the absence of nearby texture data resembling the door. This resulted in the incorrect propagation of the texture of the steps into the door region, causing a visual discontinuity that detracts from the authenticity of the restored image.
- **Texture Misalignment:**The algorithm's reliance on surrounding information led to the misapplication of step textures to the door area. This challenge underscores a limitation in the current patch-based inpainting framework, which may not always distinguish between different elements within a complex scene.

Strategies for Improvement

- **Improved Patch Selection:** Refining the patch selection process to better discriminate between distinct architectural features could prevent the misappropriation of textures. Introducing a classification system within the algorithm to identify different types of textures and structures might guide the patch selection towards more appropriate candidates.
- **Context-Aware Algorithms:** Developing more sophisticated algorithms that are context-aware and can understand the semantics of the scene may lead to better outcomes. Such algorithms would recognize that steps and doors are separate entities and thus should not share textures.

3.3.3 Bourgerag

The Bourgerag landscape, typically serene and punctuated by boats and their reflections on the water's surface, provided a unique challenge due to the dynamic nature of water and the intricacies involved in recreating its texture.

The inpainting algorithm was tasked with removing a boat from the scene [Figure 13], a complex undertaking given the boat's interaction with the water, reflections, and shadows. The removal was intended to not only erase the boat but also to reconstruct the water's surface seamlessly as if the boat was never there.

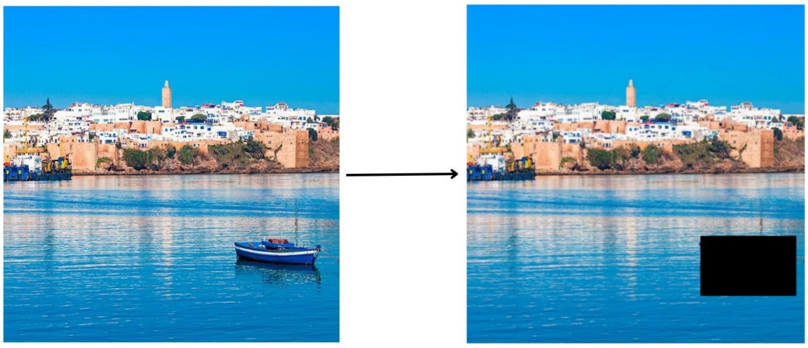

Figure 13: Masking the boat from the Bourgerag scene.

The outcome demonstrates a significant transformation, where the area previously occupied by the boat now displays a coherent continuation of the water pattern.

Figure 14: Result of the inpainting.

- **Effectiveness in Element Removal:** The algorithm's success in removing the boat was evaluated based on how convincingly the water surface was restored. This involved assessing the continuity of water patterns, the natural appearance of ripples and reflections, and the overall integration of the inpainted area with the surrounding waterscape.
- **Challenges Encountered:** The reconstruction of the water surface was imperfect, due to the complexity of matching the water's texture, reflections, and movement patterns. Such imperfections can arise when the algorithm selects patches that fail to capture the dynamism and translucency of the water or when it overemphasizes certain textures, leading to a less natural-looking surface. To mitigate these issues, post-processing techniques such as texture blending and color correction can be applied. Texture blending methods, such as Poisson blending, can help smooth out transitions between inpainted regions and the original image, resulting in a more seamless integration of the restored water surface.

3.3.4 Zellij Patterns

Zellij patterns, with their complex geometric designs and vibrant colors, represent a particularly challenging subject for exemplar-based inpainting due to their detailed and repetitive nature. The algorithm was put to the test on these patterns to evaluate its capability to replicate and restore such intricate designs without compromising the overall aesthetic. The application of the exemplar-based inpainting

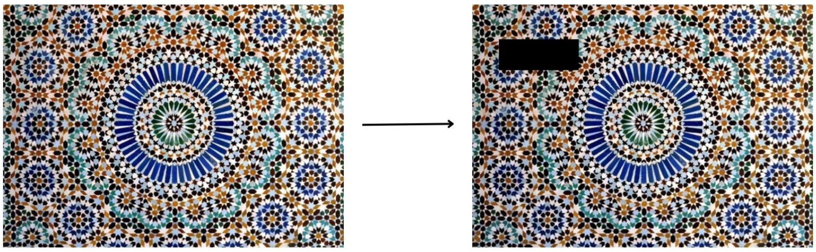

Figure 15: Mask Application on a Zellij pattern.

algorithm to the Zellij patterns resulted in a partial success [Figure 16]. The algorithm proved capable of replicating the geometric patterns within the Zellij tiles, adhering to the color and texture to a certain degree.

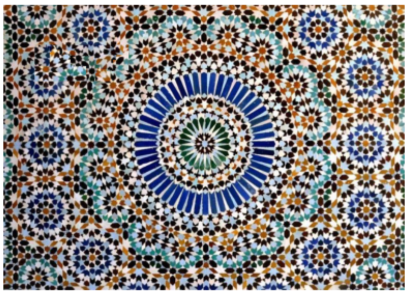

Figure 16: Results on a Zellij pattern.

- **Challenges in Geometric Symmetry:** Despite this initial success, the algorithm struggled to grasp the intrinsic geometric symmetry that defines Zellij art. The lack of symmetry in the results, when compared with the original image, was noticeable. This symmetry is essential in Zellij patterns, as it reflects the traditional craftsmanship that follows strict rules to create the intricate designs.
- **Recognition of Pattern Integrity:** The fundamental limitation observed was the algorithm's inability to discern and maintain the overarching symmetrical patterns that are critical to Zellij. While individual tiles were recreated, the holistic pattern, which is a hallmark of Zellij work, did not emerge cohesively in the inpainted area.

Inpainting Results for Zellij Patterns with a Symmetry-Focused Method By implementing a symmetry-focused technique, the results improved significantly [Figure 17]. The inpainting became more consistent with the original pattern, maintaining the aesthetic and structural integrity that is central to Zellij art. The application of the symmetry-based method demonstrated the capability to achieve geometric consistency within the inpainted area. The mirrored patch effectively recreated the damaged section, making the intervention almost imperceptible.

However, the method assumes a vertical axis of symmetry, which may not always align with the artwork's actual symmetrical properties. Future work could involve developing a more dynamic approach to determine the axis of symmetry based on the pattern's orientation.

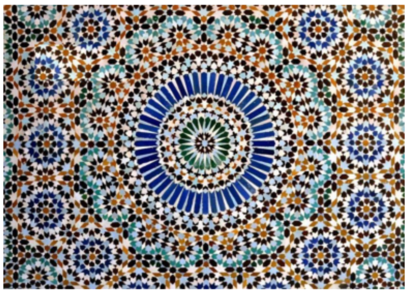

Figure 17: Results of a symmetry-focused inpaiting on a Zellij pattern.

Moreover, Zellij patterns can exhibit multiple axes of symmetry. Expanding the current method to identify and utilize different axes for inpainting could allow for a more versatile and accurate restoration across various Zellij designs.

To further enhance inpainting accuracy, integrating this method with advanced pattern analysis techniques could lead to even more refined results.

4 Conclusion

This project embarked on an exploration of exemplar-based inpainting, a method pivotal for object removal and image restoration, across various contexts—from simple binary and RGB images to the intricate textures of Moroccan historical landscapes and the detailed patterns of Zellij art.

- The algorithm showcased promising results on binary images, proving its basic functionality in scenarios with high-contrast and straightforward textures.
- RGB images introduced color complexity, where the algorithm successfully maintained color integrity but faced challenges in areas where multiple colors met.
- The application to real-world images demonstrated the method's potential in cultural heritage preservation, with effective removal of modern elements from historical sites. However, areas with complex interactions, such as shadows and detailed structures, highlighted the need for more advanced techniques.

Reflection on Project Significance: This project not only underscores the capabilities of current computer vision techniques but also illuminates the path forward for the field. The ability to digitally restore and preserve cultural heritage opens new doors for historians, educators, and conservationists, providing tools to protect and celebrate our global heritage in the digital age.

Future Directions: The journey of refining inpainting methods is far from over. The following avenues present exciting opportunities for future research:

- The development of adaptive algorithms that can recognize and adjust to various complexities within an image, such as different textures or symmetrical patterns.
- The integration of artificial intelligence, particularly machine learning models that can learn from a vast dataset of textures and patterns to improve inpainting accuracy.
- Hybrid approaches that combine algorithmic efficiency with the discerning eye of human experts, particularly in the domain of art restoration.

In conclusion, this project has demonstrated the potential of computer vision to recreate the past and the complexities involved in applying such technology to diverse and intricate images. As the algorithms become more sophisticated and tailored to the specific needs of different types of images, the applications of this technology will undoubtedly expand, further bridging the gap between art and science.

References

[1] Criminisi, A. and Perez, P. and Toyama, K, *Region filling and object removal by exemplar-based image inpainting*, *IEEE Transactions on Image Processing*. vol. 13, pp.1200-1212 2004 https://doi.org/10.1109/TIP.2004.833105