UNIVERSITÉ CÔTE D'AZUR

Multidisciplinary Project

Analysis of Aerial Images for Marine Ecosystem Protection

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1 Abstract

This multidisciplinary project focuses on leveraging drone technology and advanced computer vision techniques to support the conservation of these ecosystems. Specifically, two key aspects were addressed: the development of a comprehensive requirements document for optimal aerial image acquisition and the implementation of image stitching algorithms to create panoramic views of surveyed areas.

The requirements document establishes guidelines for flight conditions, camera specifications, and environmental considerations to ensure high-quality data capture. In parallel, the stitching process utilized Scale-Invariant Feature Transform (SIFT) and Brute-Force Matching (BFMatcher) for feature extraction and alignment, producing cohesive panoramas. While results were promising for synthetic images with distinct features, challenges arose with real-world marine images due to low feature density and homogeneity.

2 Introduction

This multidisciplinary project typically involves students from diverse academic backgrounds, especially those from the MARRES program. However, this year, no students from the MARRES program participated in the project. The team consisted of two Master's students in Computer Science: **Shanti NOEL** and myself. We worked on two separate directions, resulting in two separate reports.

2.1 Context

Posidonia play a crucial role in Mediterranean marine ecosystems. These underwater grasslands, vital for biodiversity, serve as refuges and breeding grounds for numerous marine species, while contributing to seabed stabilization and carbon sequestration. However, these fragile ecosystems are under threat from human activities such as boat anchoring, pollution, and climate change, leading to a gradual decline in their coverage. The Lérins Islands, located off the coast of Cannes, represent an area where Posidonia is particularly affected. Anthropogenic pressure, especially from ship anchoring in the Frioul Channel, poses a direct threat. It has become imperative to monitor these ecosystems to assess the impact of human activities and develop appropriate conservation strategies. Drone technology, combined with advanced computer vision methods, offers a unique opportunity to monitor these ecosystems effectively. Aerial images captured by drones provide detailed data on the extent of the meadows, facilitating their analysis and mapping.

2.2 Objectives

In this project, my contribution focused on two major technical aspects. First, I worked on developing a specification document to define the ideal conditions required for capturing usable aerial images with drones. This task involved an in-depth analysis of flight parameters, such as altitude, image overlap, and optimal weather conditions, as well as technical specifications of equipment like camera resolution and drone stability. The specifications also integrated environmental and regulatory constraints to ensure an approach that is respectful of marine ecosystems and compliant with current laws.

In parallel, I focused on image stitching to merge multiple aerial photographs into a coherent panorama. This work required the implementation of advanced computer vision algorithms, such as SIFT for keypoint extraction and BFMatcher for feature matching. The main objective was to produce usable panoramic images for mapping Posidonia meadows while minimizing distortions and ensuring maximum accuracy. These two contributions aim to provide essential tools and data to support the monitoring and preservation of marine ecosystems in the Lérins Islands region.

2.3 State of the Art

In the field of image stitching, algorithms like RANSAC (Random Sample Consensus) are often used alongside feature matching techniques to adjust geometric transformations between images. Moreover, modern frameworks such as OpenCV offer pre-built pipelines for photogrammetry but require careful adaptation to the specificities of marine data. These technologies must also be tailored to environments with few visual reference points, a common challenge in homogeneous marine settings, such as sandy seabeds.

Similarly, specification documents for drone missions rely on evolving standards to integrate both technical specifications and ecological imperatives. These advances underscore the importance of an interdisciplinary approach, combining computer science and ecology to address the challenges of marine ecosystem preservation.

3 Materials and Methods

3.1 Specification Document

To ensure the capture of usable drone images, a rigorous specification document was developed based on the following points:

Weather Conditions:

- Wind speed below 20 km/h to minimize vibrations.
- Optimal brightness: flights conducted between 10 a.m. and 3 p.m. to avoid long shadows.
- No precipitation: Humidity and raindrops can affect image quality.

Flight Parameters:

- Altitude: 25-50 meters for a compromise between resolution and coverage.
- Trajectory: Grid-based itinerary systematically covering the study area.

Equipment Specifications:

- Camera resolution: minimum 20 megapixels.
- RTK sensors for enhanced GPS accuracy.
- Polarizing filter to reduce water reflections.

Environment and Safety:

- Respect for regulated areas.
- Altitude compliant with legal limits: maximum of 50 meters.
- Measures to minimize environmental impact (reduced noise, flights outside marine species' breeding periods).

3.2 Parametric Calculations for Drone Mission Planning

To ensure optimal coverage of the study area, I developed a module to evaluate several critical parameters related to the drone and its camera. This module simulates ground coverage and estimates the number of images required to map a given area. The calculations are based on parameters such as flight altitude, focal length, sensor dimensions, and the horizontal and vertical resolutions of the camera.

The calculations are based on the following formulas:

Ground Coverage and Resolution:

The cameras horizontal and vertical fields of view (FOV) are calculated from the focal length and sensor dimensions. These values are then used to determine the width and height of the area covered by a single image on the ground at a given altitude.

$$\begin{aligned} \text{ground\_width} &= 2 \times \text{altitude}_h \times \tan\left(\frac{FOV_{\text{horizontal}}}{2}\right) \\ \text{ground\_height} &= 2 \times \text{altitude}_h \times \tan\left(\frac{FOV_{\text{vertical}}}{2}\right) \\ \text{GSD}_{\text{horizontal}} &= \frac{\text{ground\_width}}{\text{horizontal\_resolution}} \\ \text{GSD}_{\text{vertical}} &= \frac{\text{ground\_height}}{\text{vertical\_resolution}} \end{aligned}$$

Estimating the Number of Images Required:

Based on the dimensions of the area to be mapped, the total surface area is divided by the surface area covered by a single image to estimate the number of images needed. This estimate represents whole images, so additional images are necessary to ensure sufficient overlap for stitching.

$$\begin{aligned} \text{Total Area} &= \text{zone\_width} \times \text{zone\_height} \\ \text{Number of Images} &= \frac{\text{Total Area}}{\text{ground\_width} \times \text{ground\_height}} \end{aligned}$$

3.3 Image Stitching

The image stitching process consists of three main steps: keypoint extraction, feature matching, and geometric transformation calculation. These steps enable the merging of multiple images captured from different angles into a coherent panoramic image.

3.3.1 Keypoint Extraction and Descriptors

To detect distinctive and representative regions in each image, the SIFT (Scale-Invariant Feature Transform) algorithm was used. This algorithm is particularly suitable for images containing complex textures, such as marine ecosystems. It identifies keypoints that remain invariant to geometric transformations (rotation, scaling) and variations in brightness. Each keypoint is associated with a descriptor vector encapsulating information about its immediate neighborhood.

Comparison of SIFT with Other Methods:

- SURF (Speeded-Up Robust Features): Faster than SIFT but less precise for detecting complex features or images with significant rotation or perspective variations.
- ORB (Oriented FAST and Rotated BRIEF): Faster and computationally less expensive, but descriptors are less discriminative, leading to incorrect matches.
- BRISK (Binary Robust Invariant Scalable Keypoints): Designed for speed but lacks robustness in complex transformations or scale variations.

Before applying this algorithm, the images were converted to grayscale to reduce computational complexity while retaining essential information for keypoint detection.

The algorithm returns the set of keypoints in an image and their descriptors. Keypoint descriptors play a crucial role in computer vision because they enable the comparison and recognition of keypoints between different images. After detecting keypoints, their positions alone are insufficient for identification or matching. Descriptors, which are fixed-length numeric vectors, encapsulate unique characteristics of the surrounding region of a keypoint, such as pixel intensity in specific directions or dominant orientations.

They are crucial to ensure that extracted keypoints remain comparable even when images undergo transformations such as translation, scaling, or brightness variations, which are common with drone-captured images. For instance, two images of the same object captured under slightly different angles or sizes will produce keypoints that appear similar, but descriptors will help identify them as the same.

Here is an example of detected keypoints in two images:

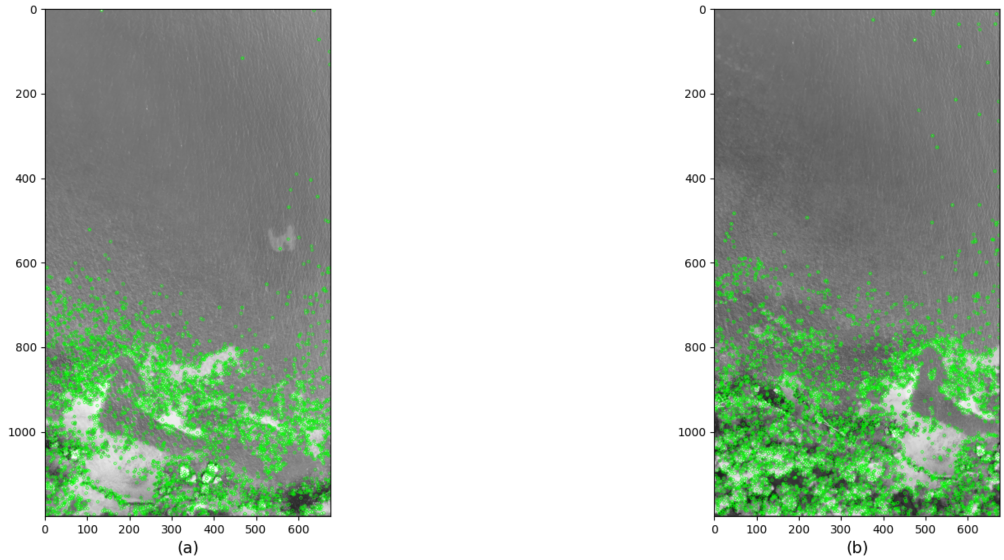

Figure 1: Keypoints

3.3.2 Feature Matching

Once the keypoints and their descriptors are extracted, it is necessary to find matches between images. This was achieved using the Brute-Force Matching (BFMatcher) algorithm. This algorithm compares the descriptors of keypoints in one image with those in another to find the most similar pairs.

```
bf = cv2.BFMatcher(cv2.NORM_L2, crossCheck=crossCheck)
```

Figure 2: BFMatcher

To improve robustness, a K-Nearest Neighbors (KNN) method was used as a complement. This method applies a ratio test to filter out dubious matches, ensuring that only the most reliable keypoint pairs are retained.

```
rawMatches = bf.knnMatch(features_train_img, features_query_img, k=2)
```

Figure 3: KNN Matching

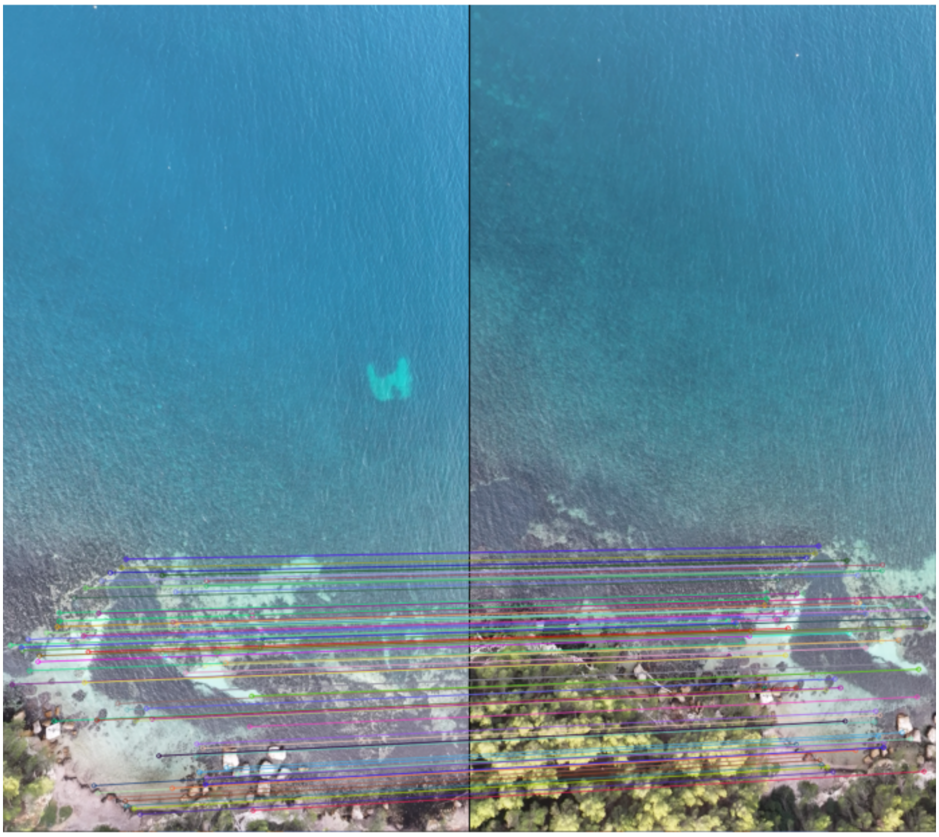

Figure 4: Keypoints Matching

3.3.3 Homography Calculation

After identifying valid matches between images, a homography matrix is calculated to align the images. This matrix describes a geometric transformation that projects one image onto the coordinate system of another. The RANSAC (Random Sample Consensus) algorithm was used to estimate this matrix while rejecting incorrect matches. This ensures that distortions such as rotations, translations, or perspective changes are accurately corrected.

3.3.4 Image Fusion

Finally, the images are merged by applying the calculated transformation. The `cv2.warpPerspective` function is used to project the images onto a single canvas, adjusting overlapping areas to minimize visual artifacts.

4 Results

The results obtained show varying performance depending on the characteristics of the processed images. These variations are mainly due to the nature of the extracted keypoints and the complexity of the scenes.

4.1 Synthetic Images (e.g., Mario Bros Level)

For synthetic images containing many well-defined points of interest, such as those from the Mario Bros level, the results are generally satisfactory. The algorithms effectively detected and matched keypoints thanks to the distinct textures and patterns in these images. The generated panoramas demonstrate good geometric coherence, with precise alignments between images and few visual artifacts in overlapping areas. These results show that the pipeline performs well when images are rich in exploitable details. However, despite successful stitching, panorama quality deteriorates as more images are assembled, making the images difficult to use on a large scale.

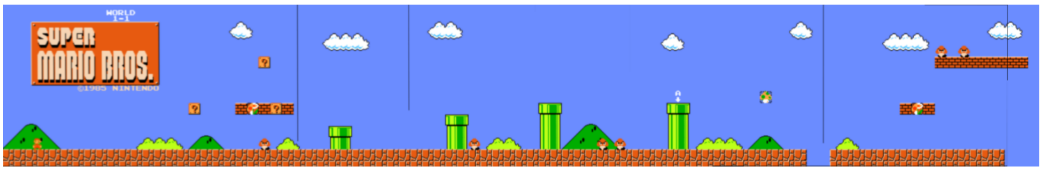

Figure 5: Stitching: 9 Images

Figure 6: Stitching: 17 Images

4.2 Real Images (e.g., Marine Surfaces)

In contrast, the pipelines performance deteriorates when processing real images of the sea, particularly those captured over Posidonia meadows or homogeneous marine areas. These images contain few distinct points of interest, significantly limiting the effectiveness of keypoint extraction algorithms like

SIFT. Matches between images are less numerous and less reliable, often resulting in poorly aligned or distorted panoramas.

Challenges Encountered Include:

- **Lack of Distinct Textures:** Marine surfaces offer little variation in brightness or patterns, making keypoint detection difficult.
- **Poor Matches:** Due to image homogeneity, descriptor matches are often erroneous, leading to distortions in geometric transformations.
- **Unaligned Areas:** In some cases, adjacent images fail to connect correctly, creating visible discontinuities in the panoramas.

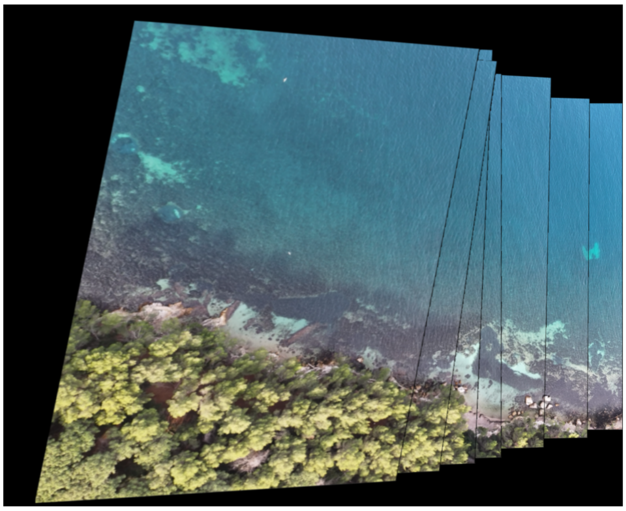

Figure 7: Stitching: 7 Images

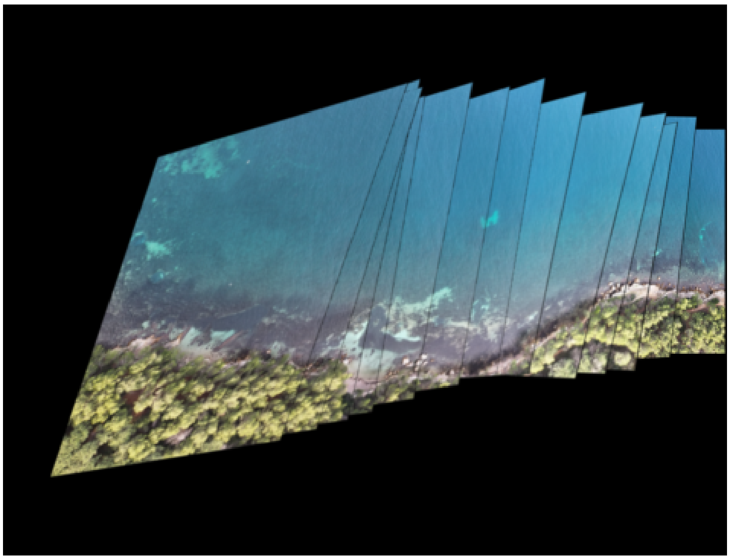

Figure 8: Stitching: 13 Images

These results highlight the limitations of traditional computer vision algorithms in contexts where images contain few distinctive features. Although algorithms like SIFT are robust to certain geometric transformations and contrast variations, their effectiveness decreases significantly when applied to homogeneous environments such as marine surfaces.

5 Conclusion

The work presented in this report aimed to contribute to the protection of marine ecosystems, particularly Posidonia meadows, through two main axes: developing a specification document for aerial image capture using drones and advancing image stitching techniques. These two areas laid the foundation for precise ecological monitoring using modern technologies.

On one hand, the specification document provided a rigorous framework to optimize drone missions, considering environmental constraints and technical specifications. The parametric calculations offered accurate estimates of ground coverage and the number of images required, ensuring efficient planning.

On the other hand, image stitching demonstrated varying performance depending on the types of images. Results were satisfactory for scenes rich in points of interest, such as Mario Bros levels, where the SIFT algorithm effectively extracted robust matches and generated coherent panoramas. However, results for real marine images were more limited due to surface homogeneity and lack of distinctive features. This led to challenges in keypoint extraction, less reliable matches, and distortions in panoramas.

5.1 Perspectives and Future Work

The limitations observed in processing real images open avenues for future improvements, including:

- Integrating deep learning algorithms capable of detecting complex and specific features in marine environments.
- Using multispectral or hyperspectral images to better differentiate meadows from other marine surfaces.
- Refining keypoint detection and matching parameters to improve robustness in homogeneous environments.

6 Acknowledgments

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