UCalib: Cameras autocalibration on coastal video monitoring systems

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Abstract: Following the path set out by “Argus” project, video monitoring stations have become a very popular low cost tool to continuously monitor beaches around the world. For these stations to be able to offer quantitative results, cameras must be calibrated. Cameras are usually calibrated when installed and, at best, extrinsic calibrations are performed from time to time. However, intra-day variations of camera calibration parameters due to thermal factors, or other kind of uncontrolled movements, have shown to introduce significant errors when transforming the pixels to real world coordinates. Departing from well known feature detection and matching algorithms from computer vision, this paper presents a methodology to automatically calibrate cameras, in the intra-day time scale, from a small number of manually calibrated images. For the three cameras analyzed here, the proposed methodology allows for automatic calibration of > 90% of the images in favourable conditions (images with many fixed features) and ~ 40% in the worst conditioned camera (almost featureless images). Results can be improved increasing the number of manually calibrated images. Further, the procedure provides the user with two values that allow to assess the expected quality of each automatic calibration. The proposed methodology, here applied to Argus-like stations, is applicable e.g., in CoastSnap sites, where each image corresponds to a different camera.

Keywords: Video monitoring stations for beaches; video stabilization; feature detection and matching algorithms.

1. Introduction

Coastal managers, engineers and scientists need coastal state information at small scales of days to weeks and meters to kilometers [1]. Among many other, the reasons are determining storm impacts [2], monitoring beach nourishment performed to mitigate coastal erosion [3], recognizing rip currents [4] or estimating the density and daily distribution of users in the beaches during summer [5]. In the early 1980s, video remote sensing systems were introduced for monitoring of the coastal zone [6–9] in order to obtain data with higher temporal resolutions and lower economical and human efforts than the ones required by traditional field studies. Qualitative information about the beach dynamics [10] or the presence of hydrodynamic [11] and morphological [12] patterns can be obtained from raw video images. Images have also been used, in a quantitative way, to locate the shoreline and study its evolution [13–15], to determine the intertidal morphology [16–18], to estimate the wave period, celerity and propagation direction [19,20], or to infer bathymetries [21,22]. For these latter applications, in which magnitudes in physical space are required, accurate georeferencing of images is essential [23,24].
The transformation of images (2D) to real physical space (3D) is usually performed following photogrammetric procedures in which the characteristics of the optics (intrinsic parameters) and the location and orientation of the camera (extrinsic parameters) have to be obtained [25,26]. Intrinsic calibration yields optics parameters of the camera (distortion, pixel size and decentering) and allows to eliminate image distortion induced by the camera lens. Extrinsic calibration allows to determine the camera position \((x_c, y_c, z_c)\) and orientation \((\phi, \sigma, \tau)\), Figure 1, which allow to associate each pixel of the undistorted image with real world coordinates (provided, usually, the elevation \(z\)). Extrinsic calibrations are obtained using Ground Control Points (GCPs, pixels whose real-world coordinates are known). The GCPs can also be used for intrinsic calibration, which is often obtained experimentally in laboratory [27–29]. Generally, Argus-like video monitoring systems are fully (intrinsic and extrinsic) calibrated at the time of installation, and then extrinsic calibrations are performed at a certain frequency [bimannually, e.g., 14] or when a significant camera movement is noticed. However, it has already been observed that calibration parameters change throughout the day for a variety of reasons including thermal and wind effects [30–32], as well as over longer time periods, due to natural factors and/or human disturbance [32,33]. If the calibration of all individual images is not adjusted, quantitative information obtained could have a significant error, leading to inaccurate quantification in shoreline trends, hydrodynamic data such as longshore currents, wave celerity or runup and, in turn, nearshore bathymetries.

Although the importance of intra-day fluctuations was already reported by Holman and Stanley [30] in 2007, this problem has been disregarded in most studies with coastal video monitoring systems. Recently, Bouvier et al. [32] analyzed, in a station consisting of 5 cameras, variations in the orientation angles of each of the cameras during one year. From the manual calibration of about 400 images per camera, they identified the primary environmental parameters (solar azimuthal angle and cloudiness) affecting image displacements and developed an empirical model to successfully correct the camera motions. This approach has the disadvantage that it does not automatically correct variations over long periods of time, in addition to requiring manual calibration of a large number of images. In order to achieve the highest number of calibrated images while minimizing human intervention, the strategy followed in other studies [31,33–35] has been to automatically identify objects and to use their location in calibrated images for their stabilization.

Pearre and Puleo [31] located some features at selected Regions Of Interest (ROI) from a distorted calibrated image into other images to obtain the relative camera displacements between images and then recalculate the orientation of the cameras (tilt and azimuth angles) for each image. Relative shifts of the ROIs were then obtained by finding the correlation peak of correlation matrices. Accurate recognition of pixels corresponding to GCPs in images, using automatic algorithms such as SIFT (Scale-Invariant Feature Transform, [36,37]) or SURF (Speeded-Up Robust Features, [38]), allowed not only to re-orient the cameras but also to compute extrinsic calibration parameters of each individual image [34,35]. Recently, Rodriguez-Padilla et al. [33] have proposed a method to stabilize 5 years of Argus-like station images by identifying fixed elements on images and then correcting the orientation of the cameras by computing deviations with respect a reference image. In this study, CED (Canny Edge Detector, [39]) is used to identify permanent features, such as corners or salients, under variable lighting conditions at given ROIs. In all imaging stabilization studies carried out to date in the coastal zone, it is assumed that identifiable features are permanently present, which are used to correct the orientation of cameras or to carry out the complete calibration of the extrinsic parameters. However, in many Argus-like stations, when installed in natural environments such as beaches or estuaries, the number of fixed features is very limited or non-existent over long periods.

In this paper we explore image calibration by automatically identifying arbitrary features, i.e., without pre-selection, in the images to be calibrated and in previously calibrated images. Provided that fixed features will be considered very limited, it will not be possible to calibrate the images on the standard GCPs approach, as it is done in [24]. Alternatively, we relate pixels of pairs of images through homographies, the main assumption of this work being that the position of the camera position is
nearly invariant. As a counterpoint, there is no need to impose any constraint on either the intrinsic
 calibration parameters of the camera (lens distortion, pixel size and decentering) or on its rotation. The
 automatic camera calibration is applied to three video monitoring stations. Two of them operate on
 beaches of the city of Barcelona (Spain), where there are many fixed and permanent features, and the
 third one on the beach of Castelldefels, located southwest of Barcelona, where the number of fixed
 points is very limited.

The main aim of this paper is to present a methodology to, departing from a small set of manually
 calibrated images, automatically calibrate images without the need of prescribing reference objects
 and to evaluate their feasibility. Next Section 2 presents the basics of mapping pixels corresponding to
 arbitrary objects between images and the methodology to process points in pairs of images in order to
 obtain automatically the calibration of an image. Section 3 presents the results that will be discussed in
 Section 4. Section 5 draws the main conclusions of this work.

2. Methodology

2.1. Camera equations and manual calibration

Given the real world coordinates of a point, \( x = (x, y, z) \), the corresponding (distorted) pixel
coordinates, column \( c \) and row \( r \) (Figure 1), are given by

\[
c = \frac{u}{s} (1 + k_1 d^2) + o_c, \quad r = \frac{v}{s} (1 + k_1 d^2) + o_r,
\]

where \( k_1 \) stands for radial distortion, \( s \) for pixel size (the pixel is assumed squared), \( o_c \) and \( o_r \) are the
pixel coordinates of the principal point (considered herein at the center of the image), \( d^2 = u^2 + v^2 \)
and \( u \) and \( v \) are the undistorted coordinates in the image plane

\[
u = \frac{(x - x_c) \cdot e_u}{(x - x_c) \cdot e_f}, \quad v = \frac{(x - x_c) \cdot e_v}{(x - x_c) \cdot e_f},
\]

where \( x_c = (x_c, y_c, z_c) \) is the camera position (or “point of view”) and \( e_u, e_v \) and \( e_f \) are orthonormal
vectors defined by the camera orientation, i.e., by the eulerian angles \( \phi \) (azimuth), \( \sigma \) (roll) and \( \tau \) (tilt) in
Figure 1.

![Figure 1. Real-world (x, y, z) to pixel (c, r) transformation: camera position (x_c, y_c, z_c) and eulerian angles (\( \phi \), \( \sigma \) and \( \tau \)).](image)

Equation (1) represents a reasonable simplification of more complex distortion models: radial
distortion has been assumed parabolic and tangential distortion neglected. This simplified model
has shown to be able to model the distortion of common nowadays cameras [40] and, in particular,
the cameras considered in this work. The eight free parameters of the model are the camera position, \( \mathbf{x}_c = (x_c, y_c, z_c) \), the three eulerian angles (\( \phi \), \( \sigma \) and \( \tau \)), as well as \( k_1 \) and \( s \).

**Manual calibration of a single image**

Given an image, the eight free parameters of the model can be obtained from a set of \( N \) Ground Control Points (GCPs), pixels of the distorted image whose real-world coordinates are known, i.e., \( N \) tuples \( (c_n, r_n, x_n, y_n, z_n) \) with \( n = 1, \ldots, N \). The free parameters can be found by minimizing the reprojection error [see, e.g., 41]

\[
\varepsilon_G \text{[pixel]} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left[ (c'_n - c_n)^2 + (r'_n - r_n)^2 \right]},
\]

where \( c'_n \) and \( r'_n \) are the values obtained from \( (x_n, y_n, z_n) \) using model equations (1) and (2) with the proposed parameters. Whenever the horizon line can be detected, it can also be introduced in the optimization process by minimizing \( \varepsilon_T = \varepsilon_G + \varepsilon_H \), where \( \varepsilon_H \) is the horizon line error: the root mean square of the distances from the pixels detected in the horizon and the horizon line as predicted by the calibration parameters (see, e.g., [42]). Hereafter we will refer to error \( \varepsilon_T \) whether or not the horizon line is detected, assuming that \( \varepsilon_H = 0 \) if the horizon line is not available.

**Manual calibration of a set of images**

A set of \( J \) images, for which GCPs and, in some cases, horizon line pixels are available, is calibrated by minimizing the total error of the set, i.e. \( \sum_{j=1}^{J} \varepsilon_T \). We consider here three different approaches:

- **Case 0**: Different values of \( \phi, \sigma, \tau \) for each image, and common values for \( x_c, y_c, z_c, k_1, s \) (3\( J \) + 5 unknowns).
- **Case 1**: Different values of \( \phi, \sigma, \tau, k_1, s \) for each image, and common values for \( x_c, y_c, z_c \) (5\( J \) + 3 unknowns).
- **Case 2**: Different values of \( x_c, y_c, z_c, \phi, \sigma, \tau, k_1, s \) for each image (8\( J \) unknowns).

### 2.2. Homographies

Consider now two images captured at the same point of view (“A” and “B” in Figure 2), but with a different orientation of the camera (case 0) or, even, with different cameras (case 1). The points in the projective planes corresponding to the same ray, i.e., one same point in real space, can then be transformed by an “homography”. The relationship between the undistorted coordinates \( u \) and \( v \) corresponding to one spatial point as seen in two different images (“A” and “B”, with different angles and intrinsic parameters) is given by [43]
\[ u_B = \frac{H_{11}u_A + H_{12}v_A + H_{13}}{H_{31}u_A + H_{32}v_A + H_{33}} \]
\[ v_B = \frac{H_{21}u_A + H_{22}v_A + H_{23}}{H_{31}u_A + H_{32}v_A + H_{33}} \]

where \( H_{ij} \) corresponds to the \( i \)-th row and \( j \)-th column of the \( 3 \times 3 \) rotation matrix

\[ H = R_B \cdot R_A^T. \]

The rows of matrices \( R_B \) and \( R_A \) are the unit vectors \( e_u, e_v \) and \( e_f \) of images \( B \) and \( A \) respectively.

2.3. Automatic calibration

The automatic calibration of an image is performed in 4 steps that are schematized in Figure 3. First, a set of (manually) calibrated images is generated, which will be referred to as basis (step 1). Next, common features between the image to be calibrated and each of the basis images are identified (step 2). These pairs are then purged to remove erroneous matching features, and from the remaining set of features a selection is made (step 3). Finally, this selection is used to calibrate the image (step 4).

The details of each of the steps are described below. For simplicity, the automatic calibration procedure is described for case 0, i.e., when the camera position \( x_c = (x_c, y_c, z_c) \), \( k_1 \) and \( s \) are the same for all images. The case 1 will be discussed, briefly, afterwards. Table 1 summarises the parameters resulting from the automatic calibration procedure and that are used to present and discuss the results.

![Figure 3. Diagram of the automatic calibration procedure.](image)

| symbol | units | description |
|--------|-------|-------------|
| \( n_p \) | - | minimum number of common features on the basis |
| \( K \) | - | number pairs, or common features pairs on the images |
| \( f \) | pixel (undistorted) | homography-reprojection error |
| \( \varepsilon_G \) | pixel | reprojection error at the GCP |
| \( \varepsilon_H \) | pixel | reprojection error at the horizon line |

2.3.1. Basis generation

To calibrate images automatically, a set of manually calibrated images will be used. This set of images will be referred upon as “basis”. Any set of calibrated images of a camera can be considered as a basis. However, the ideal would be to have the smaller number of basis images to automatically calibrate the largest number of images. Here we propose a method to generate such a basis, but we emphasize that alternative procedures (including, e.g., cluster analysis or random selection) can be used instead.

The pool of images from which to obtain the basis will have, here, \( \sim 400 \) images covering different years, seasons and hours within the day. In a first step, using matching algorithm ORB [44], any pair of images of the pool are compared to each other. For each comparison, only the best pairs of features (according to ORB) in each cell of a \( 4 \times 4 \) grid on the image are considered. Then, the basis is made up
by adding images to it in order to maximize the number of images of the pool with at least \( n_p \) cells having common features with the basis images. The procedure continues until the number of images of the pool that have \( n_p \) cells with pairs with the basis is above 90%. The number of required pairs, \( n_p \), is based on the minimum number of pairs to perform the calibration of an image (i.e., \( n_p = 2 \) for case 0). As not all features will be useful, a higher number should be taken. Note that, the higher the \( n_p \), the more images will contain the basis.

Once the basis has been established, the manual calibration of this set of images is carried out. The positions of the camera position \( x_c = (x_c, y_c, z_c) \), \( k_1 \) and \( s \) are set. In addition, as the angles of the cameras are known for these images, their rotation matrices \( R \) and the homographies \( H \) between basis images are also known.

### 2.3.2. Feature finding

Given an image to be calibrated and one basis image, the set of pairs of pixels that according to ORB correspond to the same feature is found. Using the fact that the basis images are calibrated, the pixels identified in each of the basis images are transferred to a unique basis image, that in our case is the first basis image. Hence, a set of pairs of pixels in the image to be calibrated \( (c_k, r_k) \) and the in the first basis image \( (c_{1k}, r_{1k}) \) corresponding to the same features is obtained, with \( k = 1, \ldots, K_0 \). The number \( K_0 \) of pairs will be the sum of pairs encountered with each basis image. Figure 4 illustrates this step up to this point. Next, the values of \( k_1 \) and \( s \) and equation (1) are used to transform these pixels to undistorted coordinates in the image to calibrate \( (u_k, v_k) \) and in the first basis image \( (u_{1k}, v_{1k}) \). These pairs of undistorted coordinates must be related through an homography (equation (4)) that involves both the rotation matrix of the image to calibrate \( R \), that depends on the unknown angles \( (\phi, \sigma, \tau) \), and \( R_{1k} \), that is known.

### 2.3.3. Feature purge and selection

Automatic matching algorithms do not always succeed, as can be seen in the images of Figure 5A and 5D. Therefore, prior to the obtention of the three unknown angles, a purge of erroneous pairs of features should be done. A RANSAC (RANdom SAmple Consensus) [45] is performed to the pairs undistorted coordinates using an homography as model. In this way, a subset of \( K_1 \leq K_0 \) pairs that actually correspond to an homography is obtained (green points in Figures 5B and 5E; the red dots being disregarded). Further, for the pairs to be more uniformly distributed along the image, out of the \( K_1 \) remaining pairs, only the best pairs (according to the homography) of each cell of a \( 10 \times 10 \) grid on image to calibrate are considered (green dots in Figures 5C and 5F). As a result, \( K \leq K_1 \) features are obtained for calibration.

### 2.3.4. Homography-based calibration

From the final subset of \( K \) features it is found the rotation matrix \( R = R(\phi, \sigma, \tau) \) which minimizes a reprojection-like error function, hereafter “homography error”,

\[
f = \frac{1}{s} \sqrt{ \frac{1}{K} \sum_{k=1}^{K} \left[ (u'_{1k} - u_{1k})^2 + (v'_{1k} - v_{1k})^2 \right] },
\]

where \( (u_{1k}, v_{1k}) \) are the undistorted coordinates of the \( k \)-th feature in the first image of the basis and \( (u'_{1k}, v'_{1k}) \) is the transformation, through \( H = R_{1k} R^T \) and equation (3), of this feature in the image to calibrate to the first basis image. Recalling equation (1), the term \( s^{-1} \) has been introduced in equation (5) so that the homography error \( f \) is expressed in (undistorted) pixels. The output of the automatic calibration of an image are \( \phi, \sigma \) and \( \tau \), as well as the minimized \( f \) and the number of pairs, \( K \). These last two values, \( f \) and \( K \), will show to be helpful in assessing the quality of the automatic calibration: small homography errors \( f \) and large \( K \) should correspond to better results.
Figure 4. Illustration of the step 2. Image to calibrate (A), basis of images (B-D) and first image of the basis including all the pairs found (E).

If case 1 applies, the above algorithm remains the same except that, in order to transform \((c_k, r_k)\) to \((u_k, v_k)\) through equation (1), unknown values of \(k_1\) and \(s\) for the image to calibrate are required and have to be obtained recursively. Case 1 corresponds to CoastSnap [15], a citizen science project for beach monitoring.

2.4. Study sites and video monitoring stations

Images of three cameras from different Argus-like stations are considered in this work (Figure 6). Station BCN1 overviewed Barcelona beaches from 2001 to 2015 with a set of five cameras [14] (Figure 6A shows the one considered here, 768 \(\times\) 576 pixel\(^2\)). This set of cameras was replaced in 2015 by a set of six cameras of higher resolution (herein named station BCN2, Figure 6B, 2452 \(\times\) 2056 pixel\(^2\)) which are running nowadays. A third station, CFA1, with five cameras, is running on Castelldefels beach from 2010 [46] (Figure 6C, 1280 \(\times\) 960 pixel\(^2\)). Note that images from BCN1 and BCN2 include plenty of permanent features (wave breakers, promenades, buildings, …), which are to help in the automatic calibration.

All stations provide, every daylight hour, one snapshot as well as one timex (time average image) and one variance image [30]. The pools of timex images from which to obtain the basis were obtained with a certain time step to ensure images for all day hours. The parameters to obtain the pool of images for each camera are shown in Table 2.
Figure 5. Illustration of the step 3. Pixels in the image to calibrate (A-C) and in the first image of the basis (D-F): the $K_0$ original pixels from matching algorithms (A, D), RANSAC selection (B, E, with $K_1$ green points), grid selection out of the RANSAC points (C, F, with $K$ green points).

Figure 6. Images from BCN1 (A, 768 $\times$ 576 pixel$^2$), BCN2 (B, 2452 $\times$ 2056 pixel$^2$), and CFA1 (C, 1280 $\times$ 960 pixel$^2$) video monitoring stations (coo.icm.csic.es).

| station | from          | to           | step $x$ [hours] | # of images |
|---------|---------------|--------------|------------------|-------------|
| BCN1    | 1-jan-2002    | 1-jul-2015   | 145              | 417         |
| BCN2    | 1-jan-2016    | 1-jan-2019   | 25               | 529         |
| CFA1    | 1-jan-2011    | 1-jan-2019   | 73               | 392         |

Table 2. Pool of images: initial and final dates, time step and resulting number of images.

2.5. Code availability

The source code to calibrate a set of images from a basis of images that are calibrated manually is freely available on GitHub (https://github.com/Ulises-ICM-UPC/UCalib). The code is accompanied by descriptive documentation, and as example, the script and the corresponding images. This code performs the calibration of the basis images (step 1) and the calibration of the images (steps 2 to 4).
3. Results

3.1. Basis of images

Figure 7 shows, for BCN1 and BCN2 respectively, the evolution of the percentage of pool images with \( n_p = 4 \) (or more) cells having pairs with the basis images as new images are incorporated to it (recall Section 2.3.1). From Figure 7, the basis has 8 images for BCN1 and only 3 for BCN2 (Figures 4B to 4D). In both cases the basis images are spread over time, covering different years, months and day hours. Further, they include a variety of weather conditions.

![Figure 7. Percentage of images of the pool with \( n_p = 4 \) (or more) cells having pairs with the basis as new images are incorporated to it: BCN1 (A) and BCN2 (B).](image)

The basis of station CFA1 is built up of 20 images chosen randomly out of 40 calibrated images available. In order to have a rough idea of the capability of this basis to calibrate any given image, it has been computed the number of images of the pool that have 4 (or more) cells with pairs with the basis. The result is 44% of the 392 pool images. This value, much smaller than 90%, indicates that this basis will probably allow to calibrate a smaller percentage of images in practice.

By increasing the number \( n_p \) of required cells in the procedure proposed to obtain basis (i.e., being more demanding according to Section 2.3.1), the number of images of the basis images required to reach 90% of the pool images is increased. For example, if \( n_p = 5 \), the number of images in the basis is increased to 14 for BCN1 and 4 for BCN2. For \( n_p = 6 \), the values are 24 (BCN1) and 5 (BCN2). While trends observed for \( n_p = 4 \) (images spread over time and weather conditions) still remain, having more images in the basis should allow for the automatic calibration of a larger amount of images. This fact is confirmed in Sections 3.3 and 3.4 below.

3.2. Manual calibrations of the basis images

The basis images have been calibrated considering the three approaches in Section 2.1 (cases 0, 1 and 2). For illustrative purposes, the results for the largest basis, i.e., BCN1 for \( n_p = 6 \) (with 24 images), are shown in Figure 8. Similar results are obtained for other stations and basis.

Figure 8 shows the histograms for the 8 calibration parameters and calibration error \( \varepsilon_T \). For cases 0 and 1 the camera position \((x_c, y_c, z_c)\) collapse in a single value. For case 0 intrinsic parameters \((k_1\) and \( s)\) do also collapse. Collapsed values fall always close to the average value of the corresponding distributions, which is an indication of the results robustness. However, the most relevant issue is that errors \( \varepsilon_T \) for all three cases are very similar (the same holds for all the basis and stations, Table 3). In conclusion, the above results justify the use, hereafter, of case 0, with constant \( x_c = (x_c, y_c, z_c) \) and intrinsic parameters \( k_1 \) and \( s \).

3.3. Critical values for the homography error \( f \) and the number of pairs \( K \)

To analyze the performance of the procedure proposed in Section 2.3, and to understand how the output parameters \( f \) and \( K \) can be used to assess the quality of the automatic calibration, the procedure has been applied to sets of “control” images: images with known GCPs (and, in some cases, horizon
Figure 8. Histograms for the calibration parameters and error \( \varepsilon_T \) of the 24 images of BCN1 basis with \( n_p = 6 \) and for cases 0, 1 and 2.

| station   | case 0 | case 1 | case 2 |
|-----------|--------|--------|--------|
| BCN1 4    | 1.6 ± 0.3 | 1.5 ± 0.3 | 1.2 ± 0.3 |
| BCN1 5    | 1.5 ± 0.4 | 1.4 ± 0.4 | 1.2 ± 0.4 |
| BCN1 6    | 1.5 ± 0.3 | 1.4 ± 0.3 | 1.2 ± 0.3 |
| BCN2 4    | 1.4 ± 0.2 | 1.4 ± 0.2 | 1.3 ± 0.2 |
| BCN2 5    | 1.5 ± 0.2 | 1.4 ± 0.2 | 1.4 ± 0.2 |
| BCN2 6    | 2.2 ± 0.5 | 1.9 ± 0.3 | 1.9 ± 0.2 |
| CFA1 -    | 2.5 ± 0.5 | 2.3 ± 0.4 | 1.3 ± 0.2 |

Table 3. Mean and standard deviation of the manual calibration errors, \( \varepsilon_T \), for cases 0, 1 and 2 and for the different stations and basis.

points. For BCN1 there are 67 control images (which include the images for all basis). For \( n_p = 4 \), for which the basis has 8 images, the remaining 59 control images were automatically calibrated: Figure 9 shows the percentage of images calibrated with \( f \leq f_c \) and \( K \geq K_C \) for different values of \( f_c \) and \( K_C \). The more demanding conditions (smaller allowed \( f_c \) and larger required number of pairs \( K_C \)), the smaller the percentage of the 59 images satisfying both conditions (“successful” images). As shown in Figure 9A, for the proposed values, this percentage ranges from \( \sim 10\% \), in the most demanding condition, up to \( \sim 65\% \) in the most relaxed one.

Figure 9B shows the 95th percentile of errors \( \varepsilon_G \) and \( \varepsilon_H \) as computed from the GCPs and horizon points using the corresponding automatic calibration (for the successful calibrations). Interestingly, the 95th percentile of both errors diminish as the conditions are more demanding, i.e., as \( f_c \) decreases and \( K_C \) increases. In other words, imposed conditions on \( f \) and \( K \) are actually a good measure of the expected quality of the automatic calibration. According to Figure 9, and to equivalent results for other stations (using 46 control images for BCN2 and 20 for CFA1) and values of \( n_p \) (not shown),
Figure 9. Station BCN1 for basis with $n_p = 4$: percentage of automatic calibrations of control images so that $f \leq f_c$ and $K \geq K_C$ (A) and 95th percentile of $\varepsilon_G$ and $\varepsilon_H$ for automatic calibrations of the control images satisfying $f \leq f_C$ and $K \geq K_C$ (B).

\[ f_C = 5 \text{ pixel}, \quad K_C = 4, \quad (6) \]

seem to be a good compromise between the percentage of calibratable images and the quality of these automatic calibrations. Table 4 shows the values of percentages and 95th percentile of errors $\varepsilon_G$ and $\varepsilon_H$ of the successful control images for $f_C = 5$ pixel and $K_C = 4$ and for the different stations. From Table 4, the higher $n_p$, i.e., the more basis images, the more control images successfully calibrated.

| station | $n_p$ | success | $\varepsilon_G$ [pixel] | $\varepsilon_H$ [pixel] |
|---------|-------|---------|-------------------------|------------------------|
| BCN1    | 4     | 58% (54%) | 2.8 (3.5)               | 2.5 (5.9)              |
| BCN1    | 5     | 60% (66%) | 3.4 (3.5)               | 2.5 (5.7)              |
| BCN1    | 6     | 72% (70%) | 3.4 (3.5)               | 2.6 (4.8)              |
| BCN2    | 4     | 91% (91%) | 4.9 (4.8)               | 5.2 (5.3)              |
| BCN2    | 5     | 93% (93%) | 4.7 (4.7)               | 5.5 (5.7)              |
| BCN2    | 6     | 95% (93%) | 4.6 (5.3)               | 5.5 (5.2)              |
| CFA1    | -     | 70% (70%) | 4.5 (4.4)               | 2.0 (4.0)              |

Table 4. Percentage of success and 95th percentile of errors $\varepsilon_G$ and $\varepsilon_H$ for the successful control images for different stations and $n_p$ (for $f \leq f_C = 5$ pixels and $K \geq K_C = 4$). In parentheses, values when the horizon error is not considered in the manual calibration of the basis.

3.4. Automatic calibration of several years

Several years of images have been automatically calibrated for all three stations (see Table 5). Using the critical values proposed above ($f_C = 5$ pixel and $K_C = 4$), Table 6 shows the percentage of automatically calibrated images satisfying $f \leq f_C$ and $K \geq K_C$. While the values are different than in Table 4, the same trends are observed, namely: 1) the percentage increases with $n_p$ and 2) the worst station is CFA1 and the best one is BCN2. Table 6 also shows the results for more restrictive values ($f_C = 2$ pixel, $K_C = 5$): the percentages are smaller for these more restrictive conditions, particularly for BCN1 and CFA1.

For illustration purposes, Figure 10 shows the time evolution of the eulerian angles for BCN2 and $n_p = 4$ for $f_C = 5$ pixel and $K_C = 4$ (87% of the total images according to Table 6). In this Figure, the black dots also satisfy more demanding conditions $f_C = 2$ pixel and $K_C = 5$ (82% according to Table 6).

Most of the outliers in Figure 10, mainly observable in roll $\sigma$, correspond to red dots, i.e., those not satisfying the more demanding conditions. The signal also shows a noise which is related to intra-day oscillations (see below). This noise has, in tilt $\tau$, a seasonal behavior, with larger amplitudes in summer.
| station | from | to   | # of images |
|---------|------|------|-------------|
| BCN1    | 2002 | 2014 | 60,160      |
| BCN2    | 2016 | 2020 | 22,053      |
| CFA1    | 2013 | 2017 | 18,929      |

Table 5. Years analyzed and amount of images available for all three stations.

| station | $n_p$ | $f_C = 5$ pixel | $f_C = 2$ pixel |
|---------|------|-----------------|-----------------|
| BCN1    | 4    | 64%             | 50%             |
| BCN1    | 5    | 73%             | 61%             |
| BCN1    | 6    | 80%             | 68%             |
| BCN2    | 4    | 87%             | 82%             |
| BCN2    | 5    | 89%             | 85%             |
| BCN2    | 6    | 90%             | 85%             |
| CFA1    | -    | 44%             | 35%             |

Table 6. Percentage of automatically calibrated images satisfying $f \leq f_C$ and $K \geq K_C$ for different stations and basis and for the years in Table 5.

than in winter. Several permanent jumps are also observed in azimuth $\phi$, the most significant at the beginning of year 2019. These jumps correspond to uncontrolled movements of the camera (due to a gust of wind, e.g.) and are not always easily detected by visual inspection of the images.

Figure 10. Time evolution of the eulerian angles obtained through automatic calibration for BCN2 with $n_p = 4$, $f_C = 5$ pixel and $K_C = 4$. Black dots further satisfy $f_C = 2$ pixel and $K_C = 5$.

Following similar procedures to those in Section 2, that allow to transform pixels coordinates from two calibrated images, all images can be represented as in, e.g., the first image of the series, i.e., images are stabilized or registered. Time averaging the resulting images and comparing the result with the time average of raw images is a usual way to verify that the stabilization (here automatic calibration) is being well done [e.g. 33]. Figure 11 shows the results for the same conditions as for Figure 10 ($n_p = 4$, $f_C = 5$ pixel and $K_C = 4$). The blurring observed in Figure 11A is very much reduced in Figure 11B (stabilized).

While obtaining the timex of stabilized images is a common way to show that automatic calibration is working properly, it does not allow for a quantification of the errors before and after the process. To
illustrate such a quantitative information, one same feature has been manually tracked in the images through the series of years (a total of 2000 positions, randomly distributed in time along the years, were obtained). The feature is the left bottom corner of the sculpture marked with a white circle in Figure 11B. Estimated error when manually tracking the feature is around 2 pixels. Figure 12A shows the distribution of the pixels coordinates: four clouds are observed, corresponding to the permanent jumps in Figure 10. The Root Mean Square (RMS) of the distances of pixels to the center of mass of the distribution is 7.0 pixel, and the elongated shape of the clouds in this Figure 12A is due to intra-day oscillations. When all pixel coordinates are stabilized to the first image using automatic calibrations, the result (Figure 12B) is a single compact cloud. The RMS of the distances to the center of mass of the distribution is reduced to 1.1 pixel, consistent with the estimation of the error when tracking the feature.

These results can be, alternatively, expressed in meters (Figures 12C and D). For this purpose, it is taken into account that the feature is at $z = 4$ m. If all clicked pixels coordinates (Figure 12A) are projected into the $xy$-plane using a constant calibration (the first one, here), the resulting distribution is shown in Figure 12C. However, if the corresponding automatic calibrations are used for each pixel, the distribution is the one in Figure 12D, whose RMS of the distances to the center of mass is 3.0 m. This RMS, noise, is due, in part, to the manual tracking procedure, but also to the possible errors in automatic calibrations. Reasonably assuming that the center of mass of the distribution in Figure 12D, at $(x, y) = (-548.56 \text{ m}, -1228.59 \text{ m})$, corresponds to the actual position of the point, the RMS of the distances in Figure 12C to this position is 16.6 m, with a maximum distance between points of the cloud being around 70 m. These errors are directly those that would be transmitted to the position of the shoreline if, e.g., the objective was to calculate the area of a beach.

4. Discussion

4.1. Camera position and intrinsic calibration

The proposed process for georeferencing images using homographies is based on the assumption that cameras remain nearly immobile. This hypothesis may seem to be contradicted by the results of this study since the full manual calibration (case 2) of basis images shows a movement of the cameras of several metres in the 3 spatial directions. These movements must be taken with caution,
Figure 12. 2D-histograms of the pixel coordinates tracking a feature before (A) and after (B) stabilization, and similar results expressed in $xy$ coordinates (C and D respectively). The colorbar stands for the frequency.

as displacements of up to 20 m meter in the horizontal and almost 10 m in the vertical are absolutely unrealistic. Manual calibration of several images forcing a common camera position (case 1) gives a camera position which corresponds approximately to the average position obtained in case 2. Calibration errors resulting from these two cases are so that the difference of the mean values of the errors is less than half of the statistical deviations of the errors (see Table 3). We understand that in the full calibration the apparent movement of the cameras was actually compensated by other parameters of the calibration (see Figure 8), mainly through the intrinsic parameters (radial distortion and pixel size). Calibrations forcing common values of the intrinsic parameters (case 0) have errors that are again equivalent to those of the other two cases. We conclude therefore that the apparent camera movements and their internal deformations can be perfectly assimilated by the changes in camera orientation. Furthermore, since the complete calibration of the camera results in unrealistic displacements, we consider that it is more appropriate to allow only changes in the camera orientation and thus avoid spurious fluctuations in the position and intrinsic parameters. The results for the three calibration approximations also validate approaches made in previous studies [e.g., 32,33] in which the camera positions were fixed without further verification.

4.2. Method applicability

The results show that the method described here can be used to calibrate automatically images from Argus-type stations from a basis of manually calibrated images. In contrast to other studies [e.g. 33], it is not necessary to predefine targets in certain regions of interest. Instead, it is feasible to use arbitrary features located in the real world with unknown exact locations. This makes the method very flexible as it does not require permanent points in the image. The only important conditions are that features must be automatically detected and that the cameras must remain motionless. Results have shown that cameras of different resolutions do not cause any major inconvenience. Neither does the fact that the environment is urban or natural, and therefore with a large number of ephemeral elements. However, a number of images could not be calibrated due to the lack of common features with basis images. It is possible that the use of other algorithms [e.g., Canny Edge Detector, 39] could improve the performance. This remains for further research.
As an extension of the present work, the same method could be used in stations where several
cameras are used to take images from a fixed position, as it is the case of the CoastSnap stations [15]. In
this case the calibrations share a unique location, but both the images from the basis and the images to
be calibrated would have different internal calibrations. In this scenario, the calibrations discussed
in Sections 2.1 and 2.3 for the specific case 1 would need to be applied. The analysis of the method
presented here on CoastSnap type stations is beyond the scope of this paper. There is also the option to
perform calibrations based on homographies when the camera position is not fixed (case 2), as occurs
for cameras mounted on UAVs. This option has not been further developed in the paper as it is a very
theoretical approach. In the case where the camera moves, the homography between different images
is only valid when the points in the real world are placed over a common plane. For some beaches, it
can be assumed that the surface is at the same height, as [24] does in a first estimation, but in general
this approximation can introduce significant errors.

4.3. Horizon line in manual calibrations

Whenever the water zone is of interest [e.g., for bathymetry inversion 21,24], it is necessary that
calibrations perform well at it. Whenever the horizon line is observable, errors $\varepsilon_H$ at the horizon give a
hint of the performance of the calibration in the water zone, far from the GCPs for calibration, and
also far from the features detected by ORB algorithm (green dots in Figures 5C and 5F) for automatic
calibration. Table 4 (errors using control images) shows the 95th percentile of the errors at the GCPs,
$\varepsilon_G$, as well as on the horizon, $\varepsilon_H$. The results of Table 4 list to manual calibrations of the basis where
the horizon line has been introduced in the optimization procedure whenever it was available. As
seen, the errors in the horizon, $\varepsilon_H$, are of the same order of the errors $\varepsilon_G$.

However, it is very often the case that the horizon is not considered in the manual calibrations. If
the basis images are manually calibrated ignoring the error in the horizon, the errors of the derived
automatic calibrations are shown in parentheses in Table 4. Considering the horizon in the calibration
of basis images has little effect on $\varepsilon_G$ but significantly reduces the errors $\varepsilon_H$. This in spite that the
automatic calibration uses the same ORB points in both cases. In other words, the better performance of
the manual calibrations of the basis in regard the horizon (and, likely, in the water zone) is transmitted
to the automatic calibrations.

4.4. Critical values for the homography error $f_C$ and the number of pairs $K_C$

When performing the automatic calibration of an image, the output consists of the calibration
parameters together with $f$ (pixels) and $K$. Based on the results on control images, it is decided that
an automatic calibration can be considered to be good if $f \leq f_C$ and $K \geq K_C$, with critical values of
$f_C = 5$ pixel and $K_C = 4$. These values have been chosen as a compromise between the percentage of
calibratable images and the quality of the calibrations for all three stations and different basis. For the
stations under consideration, these critical values seem to be essentially independent of the station and
basis. However, the values of $f_C$ and $K_C$ can be arbitrarily chosen by the user. Low $f_C$ and high $K_C$, i.e.,
more restrictive conditions, will reduce the percentage of automatic calibrations, which should be more
trustful. Figure 10 shows the results for $f_C = 2$ pixel and $K_C = 5$ (black dots), showing that most of the
outliers are avoided. In order to reduce the outliers in Figure 10 for $f_C = 5$ pixel and $K_C = 4$ (all dots,
red and black), one could alternatively try a time filtering taking into account that the characteristic
filtering time window has to be small enough not to filter the intra-day oscillations of the signal. In
addition, from the results for all three stations, the more relevant questions to obtain a large percentage
of good automatic calibrations seem to be: 1) the amount of fixed features observable in the images
(BCN1 and BCN2 give better results than CFA1) and, less, 2) the image size (BCN2 works better than
BCN1).
4.5. On the origin of the camera movements

One main result from the manual calibration of the basis is, as mentioned, that the camera position can be considered constant in time (Figure 8 and Table 3), and that all the modifications of the camera can be assumed by the three eulerian angles. This does not necessarily means that the camera is not having any movement, but that these movements can be considered sufficiently small and can be compensated by the eulerian angles. According to [32], “the viewing angle deformations are controlled by thermal deformation of the pole where they are mounted” and they propose predictive expressions to correct the viewing (eulerian) angles based on cloudiness, solar azimuth angle, ... In this work, similar to [33], the goal is not to propose such an expression for our stations, but to automatically calibrate as much images as possible departing from a basis of calibrated images.

However, once the images have been (automatically) calibrated, it can be of use to seed some light on the possible mechanisms that cause the viewing angles to change. Pretending only to be illustrative, we consider the time evolution of $\tau$ (tilt) for the five cameras in station CFA1 (Figure 13); so far, only the results for camera D in Figure 13 have been shown for CFA1. Figure 14 shows the time evolution of the demeaned angle, $\Delta\tau$, for the 5 cameras of CFA1 during 7 days in summer 2013. From the figure, the tilt behavior changes from camera to camera. Focusing on the outer cameras (A and E in Figure 13), e.g., while for camera A the tilt $\tau$ tends to increase during the daylight hours, the trend is just the opposite for camera E, suggesting that the whole concrete structure is having a (small) deflection which is captured by the cameras.

![Figure 13. Castelldefels video monitoring station (CFA1) with five cameras (A-E).](image)

5. Conclusions

In this paper, an automatic calibration procedure has been proposed to stabilize images from video monitoring stations. The proposed methodology is based on well known feature detecting and matching algorithms and allows for massive automatic calibrations of an Argus camera provided a set, or basis, of calibrated images. From a theoretical point of view of computer vision, the single hypothesis supporting the approach is that the camera position can be regarded to be nearly constant. In the cases considered here (Argus-like station), it has been proven that the intrinsic parameters and the camera position can actually be considered constant (case 0). However, the procedure proposed here is able to manage the case in which intrinsic calibration parameters change in time, which makes the approach valid for CoastSnap stations.

The number of images of the basis can be chosen arbitrarily (here through the required pairs, $n_p$) and, the higher it is, the more images can be properly calibrated. All the automatic calibrations are performed directly through the basis of images, i.e., second or higher order generations of automatic
Figure 14. Time evolution of the demeaned tilt, \(\Delta \tau\), for the 5 cameras of CFA1 in 7 summer days of 2013.

calibrations have not been considered to avoid error accumulations. Also, if the calibrations are to be applied to analyze the water zone (e.g., for bathymetric inversion), it is recommended that the horizon line is introduced as an input in the basis calibration. The proposed methodology offers the automatic calibration of an image together with the homography error \(f\) and the number of pairs \(K\), that give a measure of the reliability of the calibration itself. Imposing \(f \leq 5\) pixel and \(K \geq 4\), the percentage of calibrated images ranges from \(\sim 40\%\) for the worst conditioned case (Castelldefels beach, with very few features) to \(\sim 90\%\) (high resolution cameras in Barcelona, where there is plenty of fixed features), the errors in pixels being significantly reduced (e.g., from 7 pixel to 1 pixel in the analyzed case).

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Abbreviations

The following abbreviations are used in this manuscript:

| Abbreviation | Description                           |
|--------------|---------------------------------------|
| CED          | Canny Edge Detector                   |
| GCP          | Ground Control Point                  |
| ORB          | Oriented FAST and Rotated BRIEF       |
| RANSAC       | RANdom SAmple Consensus               |
| RMS          | Root Mean Square                      |
| ROI          | Region Of Interest                    |
| SIFT         | Scale-Invariant Feature Transform     |
| SURF         | Speeded-Up Robust Features            |

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