

Two steep multi-spectral registration using keypoint detector for gradient similarity

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Abstract

In precision agriculture it's common to use multi-sepctral camera (RGB+NIR), today the necessarily to have hight spatial resolution and numerous spectral band (6,8,+), have bring new type camera such as multi-sensor one. In order to compute spectral index and extract information such as shape, texture, ... for plants/leaves analysis. In such camera, we need to align those images and it's a challenge to provide precision registration in close view.

In this study we propose a two steep method applied to Airphen camera (6 spectral image). (i) Affine correction using pre-calibrated matrix at different height, the right matrix can be selected via internal GPS. And (ii) Perspective correction to refine the previous one, using keypoint matching between enhanced gradients of each spectral bands. The contribution of this paper are the evaluation of different type of keypoint detection and theres performances are consigned.

Keywords: Registration, Mutli-spectral imagerie, Precision farming, Feature descriptor

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1. Introduction

Image registration is the process of transforming different images of one scene into the same coordinate system. The spatial relationships between these images can be rigid (translations and rotations), affine (shears for example), homography, or complex large deformations models (due to the difference of depth between ground and leaves) [3]. The main difficulty is that multi-spectral image have wavelength with great distance between each spectral bands. Which implies (i) leaves have a different aspect depending on the spectral bands (ii) there are highly complex and self-similar structures in our images (iii) the scene are a grassland or agriculture image at different scale, which is a complex spectral scene making a hard fit for such a registration.

There is two type of registration, feature based and intensity based [11]. (i) Feature based methods use feature matching, in most of the time a bruteforce matching is used making those techniques slow, fortunately such feature set can be filtered to reduce the matching cost depending of the spatial properties we have, and a GPGPU implementation can reduce the cost of comparison. (ii) Intensity-based automatic image registration is an iterative process, and the metrics used are sensitive to determine the numbers of iteration, making such method even worth in time for precise registration, furthermore in multi-spectral domain how should require different metrics for each registered bands, making it hard to achieve.

Different studies of image alignment using multi-sensors camera like AIREPHEN exist using UAV like, some show good performance for Feature based [1, 10] with strong enhancement of feature descriptor for matching performances, other didn't and prefer to use intensity based [2] with better convergence metrics, which is slower and not necessarily robust again light variabilities.

Unless this type of article, as we know, no studies have been made under agricultural/external condition and near field of view (less than 10 meter). Those studies mainly propose features matching without large methods comparison of theres performances (time/precision), spectral band reference selection, or even pre-affine correction depending on the distance. Thus, this study propose the best combination of feature extractor and spectral reference on normalized gradients transformation, using pre-affine registration and matches filtering, evaluated at different spatial resolution.

1.1. Material

The multi-spectral imagery was provided by the six-band multi-spectral camera Airphen ¹. AIRPHEN is a scientific multi spectral camera developed by agronomists for agricultural applications. It can be embedded in different types of platforms such as UAV, phenotyping robots, etc. AIRPHEN is highly configurable (bands, fields of view), lightweight and compact. It can be operated wireless and combined with complementary thermal infrared channel and high resolution RGB cameras. The camera was configured using 450/570/675/710/730/850 nm with FWHM of 10nm. The focal lens is 8mm. It's raw resolution for each spectral band is 1280x960 px with 12 bit of precision. Finally the camera also provide an internal GPS antenna, that can be used to get the distance from the ground.

1.2. Data

Two dataset was taken at different height. We have used a "stairville LB-3s lighting stand set" like for positioning the camera at different height. Due to the size of the chessboard, the limited focus of the camera and the height of the lighting stand set, we have bounded the acquisition height from 1.6 meter to 5 meter with 20cm steep.

The first dataset is for the calibration, a chessboard is taken at different height, the corresponding data can by found in data/steep-chess/. And the figure 1 show the chessboard taken at each distance from the ground.

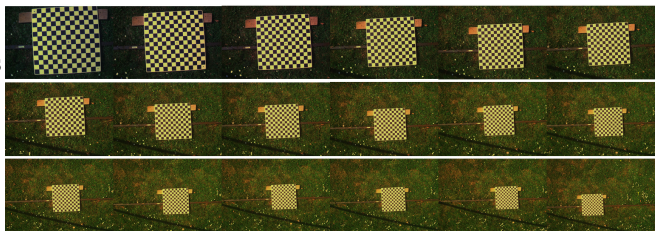


Figure 1: chessboard for calibration at different height

The second dataset for the alignment verification, one shot of a grassland is taken at different height, the corresponding data can by found in data/steep/ with a bias of +/- 10cm to be in the worth case (most complex).

¹<https://www.hiphen-plant.com/our-solutions/airphen/>

2. Method

Alignment is refined in two stage, with (i) affine registration roughly estimated and (ii) perspective registration for the refinement and precision. As example the figure 2 show each correction steep at 1.6 meter.

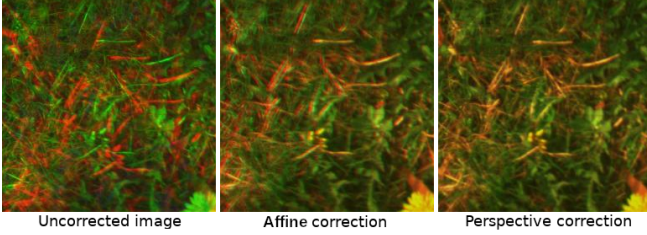


Figure 2: Example of each correction

2.1. Affine Correction

It's important to notice that closer we taken the snapshot, biggest is the distance of the initial Affine Correction. On the other hand at a distance superior or equals to 5 meter, the initial Affine Correction is near to few pixels (1-5) that is sufficient to take an identity matrix. And directly use Perspective Correction. The main purpose of this step is to reduce the distance of each spectral bands, that allow to spatially bound the similarity within few pixel, which make the feature matching more efficient.

Detect chessboard. We use opencv 4 findChessboardCorners for each spectral image (normalized) at different height (from 1.6 to 5 meter). The function attempts to determine whether the input image is a view of the chessboard pattern and locate the internal chessboard corners. The detected coordinates are approximate, and to determine their positions more accurately we use the function cornerSubPix as explained in the documentation. The detected points are ordered by x/y (detection can be flipped) and saved on data/'height'.npy

Correction. We select the detected points of the nearest height (know by the user or using the internal GPS sensor). Using all detected points for each spectral bands, we compute the centroid grid (each point mean). The affine transform from each spectral band to this centroid grid is estimated and applied. Finally all spectral bands are cropped to the minimal bbox (minimal and maximal translation of each affine matrix).

2.2. Perspective correction

Each spectral band have different properties and value by nature (figure 3), but we can extract corresponding similarity by transforming each spectral band to it's absolute derivative to find similarity in gradient break of those ones.

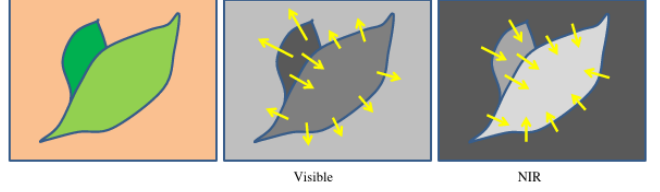


Figure 3: Gradient orientation in spectral band [6]

The previous correction, such as Affine correction attempt to help the feature matching by adding (near) epipolar line properties. So the matching of extracted feature can be spatially bounded, (i) we know that the maximal translation is bounded to few pixel distance (less than 10px), and (ii) the angle between the initial feature and the matched one are bounded to $[-1, 1]$ degree.

Computing the gradient. To compute the gradient of the image with a minimal impact of the light distribution (shadow, reflectance, ...) Each spectral bands are normalized using Gaussian blur [8], the kernel size is defined by $\text{math.ceil}(\text{image_width}^{0.4}) // 2 * 2 + 1$ (19 in your case) and the final normalized image are defined by $i / (G + 1) * 255$ where i is the spectral band and G are the Gaussian blur of those spectral band. This first step allow to minimize the impact of the noise on the gradient and smooth the signal in case of reflectance. Using this normalized image, the gradient are computed with the sum of Sharr filter [9] again $d_x = 1$ and $d_y = 1$. Different type of edge detection such as Sobel, Laplacian and Canny was tested unsuccessfully (without sufficient number of matches), those one does not appear in this study. Finally all gradients are normalized using CLAHE [12] to enhance locally theres intensity which increase the number of detected keypoints (especially for 850nm).

Keypoints Extractor. A keypoint is a point of interest. It defines what is important and distinctive in an image. Different type of keypoint extractor has been tested, all results can be found in "figures/*". These algorithms are all available and easily usable in OpenCV. For all of those algorithms we use theres default parameters. In some case, parameters are set to increase or reduce the number of keypoints (trying to have a minimum of 20 matched keypoint, and less than 500).

- ORB : An efficient alternative to SIFT or SURF nfeatures=5000
- AKAZE : Fast explicit diffusion for accelerated features in nonlinear scale spaces
- KAZE : A novel multi-scale 2D feature detection and description algorithm in nonlinear scale spaces [5]

- BRISK : Binary robust invariant scalable keypoints.
patternScale=.1
- AGAST : Adaptive and generic corner detection
based on the accelerated segment test
threshold=92, nonmaxSuppression=True
- MSER : maximally stable extremal regions
- SURF : Speed-Up Robust Features
hessianThreshold=10, nOctaves=2, nOctaveLayers=1,
upright=False
- FAST : FAST Algorithm for Corner Detection
threshold=92, nonmaxSuppression=True
- GFTT : Good Features to Track
maxCorners=5000,useHarrisDetector=True

Keypoint detection. We use one of the previous mentioned keypoint extractor on all spectral bands gradient (all extractor are evaluated). For each detected keypoint we extract descriptor using ORB features. We matches all detected keypoints to a reference spectral band (all bands are evaluated). All matches are filtered (distance, position, angle) to remove false positive one according to epipolar line. Finally we use the function *findHomography* between detected/filtered keypoints with RANSAC, to determine the best subset of matches to compute the perspective correction.

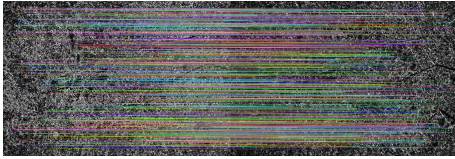


Figure 4: feature matching

Correction. The perspective correction between each spectral band to the reference is estimated and applied. Finally all spectral bands are cropped to the minimal bbox, the miniam and maximal points is get by applying perspective transform to each images corners.

3. Result and discussion

Affine correction. After the first correction, ie the Affine using matrix from the nearest calibrated height. The remaining distance between each spectral bands varies following the distance between the real height and the nearest selected. These residual distances can be see in the figure 5.

It appear that the resulted rotation and scale are not depending on the distance to the ground, but only the translation. Which expected, so single calibration can be used for this part of the matrix. For the translation part, it depend of the distance to the field, and can be

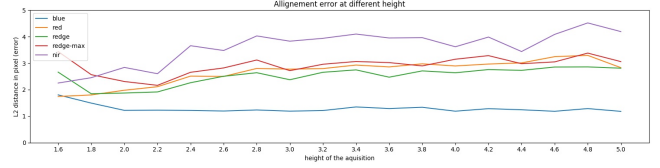


Figure 5: The mean distance of detected keypoint before perspective correction

estimated using fft correlation [7]. Due to the hard correlation between spectral band those registration especially between 450nm and 710-850nm (unless using normalized gradient) we have not investigated and suggestion the reader to see specific article [6].

Keypoint matching. The following figure 6 show the numbers of keypoint after filtering and homography association (minimum of all matches), the computation time and the performances ratio (matches/time) for each methods.

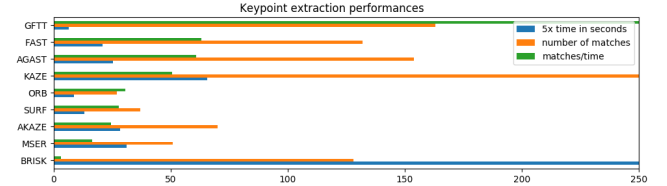


Figure 6: features performances

All this methods works, the selection of the methods depends on how we want to balance between computation time and precision:

- GFTT show the best performance over all others both in computation time and number of matches
- FAST and AGAST is the most suitable, balanced between time and matches performances.
- KAZE show the best number of matches (>200) but it's also 2.5 times slower than FAST/AGAST.
- SURF can be suitable for small gain of performances, the number of detected feature can be enough to fit the perspective correction.

The other ones did not show improvement in term of performances or matches:

- AKAZE and MSER did not show benefits comparing to FAST.
- ORB could be excluded, the number of matches is near to 20 how is the minimal to ensure that the homography is correct.
- BRISK show good number of matches, but there computation time is too huge (79 sec) comparing to FAST (8 sec).

Increasing the number of matched keypoints show tiny more precision. For example, moving from SURF (30 matches) to FAST (130 matches) show the final residual distances reduced from 1.2px to 0.9px and the computation time from 5sec to 8sec.

All methods show that the best reference spectra is 710nm, excepted for SURF and GFTT how is 570nm. The following figure 7 show the Minimum of number of matches between each reference spectra to all others using FAST algorithm. Others best spectral reference figures is available in supplementary material.

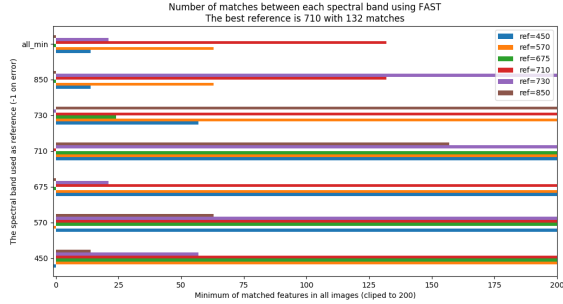


Figure 7: feature FAST performances

Perspective correction. The residuals of the perspective correction show that we have correctly registered each spectral bands with a residual error less than 1 pixel, the figure 8 show the residual distance at different ground distance.

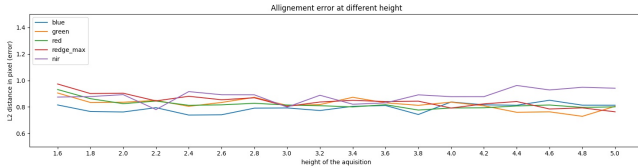


Figure 8: Perspective Re-projection Error

The following figure 9 show the difference between detected point for two bands (red-green) before (left) and after (right) the perspective correction, and show that the residual error are spatially uniform.

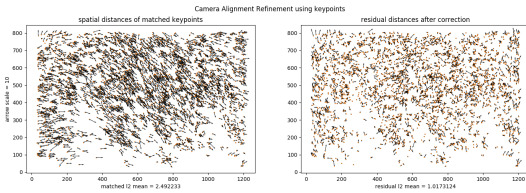


Figure 9: perspective-features-matching-scatter

Decomposing the residual distance by angle $[0 - 45 - 90 - 135 - 180 - 225 - 270 - 315 - 0]$ visible in figure 10 is interesting. You can notice that the spatial distribution

of the residual, for each different angle is equally distributed. Our hypothesis is that the nature of the base information (spectral band + different lens) make little difference on the gradient break, who is detected by the features detector and propagated to the final correction (observed residual). This is interesting stuff because this equally distributed residual by angle in the space tend to minimize the resulted correction to his center (gradient), thus the detected residual error are overrated and should be less than 0.4 pixel.

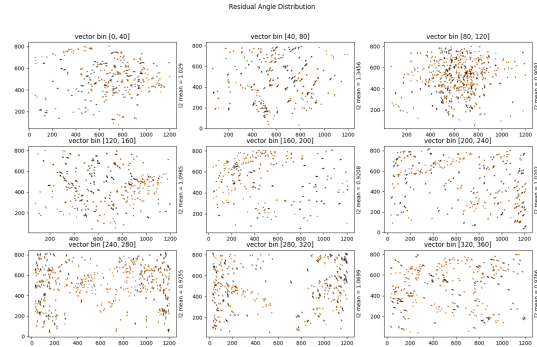


Figure 10: Residual Distribution Again Angle

However, more complex deformation model [4] can be used to enhance the remaining error. This type of complex deformation have not been fully evaluated, but only rapidly tested (cv2.ThinPlateSplineShapeTransformer). It appear no significant improvement in most of case (with huge computation time). But can also in some case create great angular deformation caused by near keypoints, of course filtering those keypoint is possible, which decrease the global precision.

4. Conclusion

In this work was explored the application of different techniques for the registration of multi-spectral images. We have tested different methods of keypoint extraction at different height and the number of control point obtained. As seen on the method, the best suitable methods is GFTT with significant number of matches with reasonable computation time. Furthermore the best spectral reference was defined for each method, such as 570 for GFTT. According to the last figure 8 we observe a residual error less than 1 px, supposedly caused by the difference of the input (spectral range, lens). Finally the method as been tested over 8000 image in real condition (not present in the study), randomly taken between 1.6 to 2.2 meter without registration error (always a minimal number of matches, without visible error, less than 0.9px).

Further research can be operated on each feature extractor parameter, for the one how need specific per-

formances (time/precision). Otherwise feature matching can be optimized, at this stage, we use brute-force matching with post filtering, but a different implementation that fulfill your epipolar line properties should greatly enhance the number of matches by reducing false positive ones.

5. Acknowledgment

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6. Supplementary material

Supplementary data and source code associated with this article can be found in the online version, at <https://gitlab.com/phd-thesis-adventice/phd-airphen-alignment> the access is limited, and we invite you to send an email to the author for a full access.

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