Normalization of ortho photos based on no-change pixels using Multivariate Alteration Detection (MAD)

Jacob S. Vestergaard, Simon G. Andersen, Allan A. Nielsen DTU Informatics & DTU Space, Technical University of Denmark

Introduction

Mosaicking of images recorded by aerial photography is a discipline with many challenges: collecting the data, choosing ortho photo model, placement of the seam line and color correction. All must be perfected in order to create goodlooking maps for e.g. Google Maps. Still, a large amount of this work is carried out using outsourced manual labour. Automated methods should be developed in order to in-source the work.

In this project we aim to color correct 16 ortho photos provided by Cowi A/S. The standard method for correcting the colors is to histogram equalize two images to each other. However, this runs the risk of using color information from pixels where a change has occured in the overlap since a previous recording, e.g. a car caught by the camera.

By applying a multivariate statistical change detection method to detect pixels where no change has occurred a more robust method for normalization of ortho photos is obtained.

Acknowledgements to Anders T. Rasmussen [4].



Detecting no-change pixels with MAD

Multivariate Alteration Detection (MAD) is a statistical method for change detection in bi-temporal, multi- and hyperspectral data [3].

This method is based on Canonical Correlation Analysis (CCA) [2]. CCA searches for linear combinations $\mathbf{U} = \mathbf{a}^T \mathbf{X}$ and $\mathbf{V} = \mathbf{b}^T \mathbf{Y}$ of the (ideally) Gaussian distributed variables $[\mathbf{X}, \mathbf{Y}] \in \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with maximum correlation

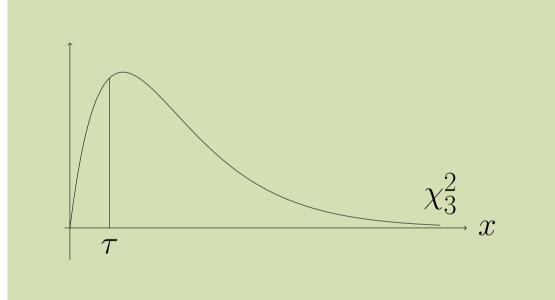
$$\rho = \operatorname{Corr}\left[\mathbf{U}, \mathbf{V}\right] = \frac{\operatorname{Cov}\left[\mathbf{U}, \mathbf{V}\right]}{\sqrt{\operatorname{Var}[\mathbf{U}]\operatorname{Var}[\mathbf{V}]}} = \frac{\mathbf{a}^T \Sigma_{12} \mathbf{b}}{\sqrt{\mathbf{a}^T \Sigma_{11} \mathbf{a} \ \mathbf{b}^T \Sigma_{22} \mathbf{b}}} \quad . \tag{1}$$

The MAD transformation [1] is defined as

$$\begin{bmatrix} \mathbf{X} \\ \mathbf{Y} \end{bmatrix} \longrightarrow \begin{bmatrix} \mathbf{a}_p^T \mathbf{X} - \mathbf{b}_p^T \mathbf{Y} \\ \vdots \\ \mathbf{a}_1^T \mathbf{X} - \mathbf{b}_1^T \mathbf{Y} \end{bmatrix}$$
(2)

which is seen to be the subtraction of the canonical variates in reverse ordering.

No-change pixel j approximately follows a χ^2 distribution:



 $T_j = \sum_{i=1}^p \left(\frac{\mathsf{MAD}_{ij}}{\sigma_{\mathsf{MAD}_i}} \right)^2 \in \chi^2(p) \; .$

1% most probable no-change pixels used for normalization.





Figure 2: Overlaps with artificial red and blue cars. MAD transformation detects both cars and changed lighting conditions on houses.

Normalizing

Results

	Before	OLS	OR
No-change pixels	1.28e3	310 (76%)	378 (71%)
Overlap	1.83e5	1.28e5 (30%)	1.44e5 (21%)

Table 1: Residual sums of squares

- A visible improvement of the color correspondence after normalization.
- Orthogonal regression performs better than OLS regression visually, but not numerically.
- Change of scene, caused by different camera angles and new items, detected in overlap using MAD.
- Large color changes within overlap provides poor results.



Original

OLS normalization

OR normalization

Ortho photos

Collected by Cowi A/S. Differences in color and intensity are primarily caused by changed flight direction and time of day.



• 3 channels: R, G, B

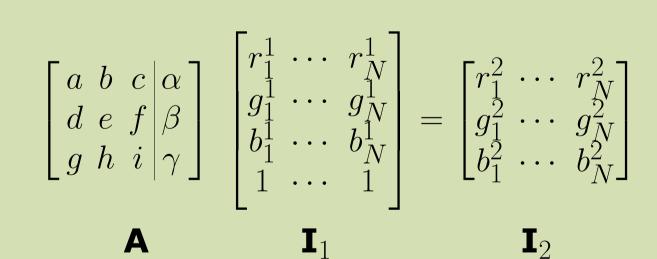
• 14650 × 9560 ≈ 140 MP

60% overlap in fligh direction20% overlap of flight lines



Figure 1: Ortho photos from Lake Tystrup

The no-change pixels found in the overlap are arranged in $3 \times N$ matrices. One of the sets is chosen as reference \mathbf{I}_2 . A transformation \mathbf{A} with an offset that adjusts the other set \mathbf{I}_1 to the reference is approximated.



The diagonal is heavily dominating the transformation matrix.

Ordinary Least Squares (OLS) regression seeks to minimize the vertical distance between an input variable and the regression line. This implicitly assumes that one of the variables is error free. Here, the reference variable is chosen arbitrarily and therefore error must be assumed on both variables.

Orthogonal Regression (OR) seeks to minimize the orthogonal distance between the observed data point and the regression line. Hereby an equal weighing of errors on both variables is achieved.

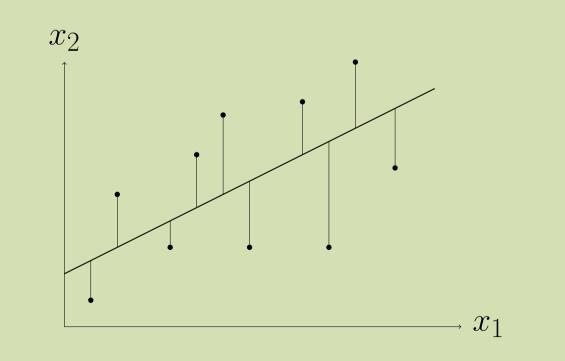


Figure 3: Ordinary Least Squares regression

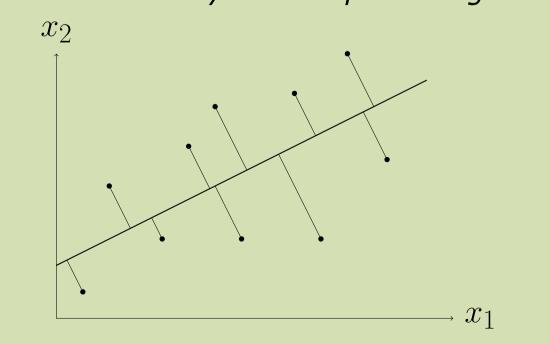


Figure 4: Orthogonal regression

Conclusions

A set of images provided by Cowi A/S have been normalized for better color correspondence.

No-change pixels in the overlaps have been used as reference for the normalization. The multivariate method MAD has been implemented to detect no-change pixels in the overlap. Ordinary Least Squares and Orthogonal Regression methods have been evaluated.

Visible improvements have been achieved from the original images to the normalized images.

Future work includes distance maps to use more overlaps, determination of a normalization sequence and implementing methods for noise filtering, e.g. Markov Random Fields.

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[2] Harold Hotelling. Relations between two sets of variates. *Biometrika*, 28(3/4):321--377, 1936.

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[4] Anders Thirsgaard Rasmussen. Color adjustment of orthophotos. Master's thesis, Technical University of Denmark, Denmark, June 2010.