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Applying of Monte Carlo Simulation to Improved Subpixel Image to Image Registration

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Abstract: This study investigates a new registration technique for remote sensing satellite images of different spatial resolutions. Existing optimization techniques assume that the accuracy of registration parameters changes by a multivariate normal form. However, when dealing with high-resolution images of highly heterogeneous land cover, the problem of no convergence can occur, this technique overcomes this problem by applying a Monte Carlo simulation. The results show a significant improvement in the correlation coefficients from R = 0.75 to R = 0.92 when a range of satellite images (Landsat_8 and Worldview 3) are used. When the registration results of multi-temporal Landsat_8 images of reduced resolution are compared with the registration of the original resolution images, the spatial accuracy witnessed a substantial improvement of 60% compared with visual registration. Although this technique may be relatively time-consuming compared with previous techniques, the results indicate that the procedure can produce a higher level of accuracy.

INTRODUCTION

Due to the fact that remote sensing has the abilities to provide relatively low-cost wide coverages with regular updates besides improvements in the advanced data processing techniques, it became one of the most widely used technologies for spatial geo-information applications. Almost all geo-information projects require the overlaying of two or more input datasets to the same coordinate system of a reference dataset to be consequential. This process of coordinate transforming is known as image registration and it can be used for multi-temporal data, multi-sensors or acquired from different viewpoints[1, 2]. Registration algorithms include four main sub-processes; it should select which mathematical processes to be used (e.g., transformation, rotation and scaling) which linking features to be used (e.g. which image subsets which pixels and which objects) which feature similarity characteristics to be used as matching criterion (e.g., pixel intensity, object size, image texture) and which optimization techniques to be used[3]. There are several methods that are used observational data to improve numerical modelling, e.g.,[4] Registration errors can have a large impact on the accuracy of the results if they are not effectively minimisation both with pixel based analysis as reported by Niel *et al*.[5, 6] and object based analysis as[7] concludes. However, the final accuracy of standard registration processes of images[8] of different spatial resolutions is proportional to the course resolution image and a more appropriate approach is to use a spectral method that works directly with the irregularly located data[9]. Therefore, an accuracy improving technique is required when it is important to guarantee that the information from each image is corresponding to the same real-life object or phenomenon. This is commonly required for systems that apply image resolution merge (data fusing), classification or visual interpretation. The available techniques for image registration of different resolutions can be classified into object based and pixel based. The object based registration requires extracting objects through image classification and/or image segmentation. Extracted features from different datasets can be matched by characteristics such as size, shape, contrast and texture to be used as reference coordinate tie points[10-12]. This registration technique allows a higher level of information abstraction. However, the accuracy of this type of registration is low with multiscale images due to the low quality of objects extracted from the lowest resolution data comparing to the quality of corresponding objects from the highest resolution image[13]. Pixel based techniques based on finding similarity in pixel's values trends either in the original images or in the transformations of images. The advantage of this type is that it uses a form of the original information. In addition, its algorithms are easier to applied and more time efficient[8].

Unlike with application of limited size images like biomedical imaging, and microscopy, the earth observation data normally have huge data sizes. Therefore, the available automated registration techniques are computationally expensive with the remote sensing based projects[3]. As a result, human intervention is acceptable to the select an initial condition. There are a number of conventional registration methods available. One of these methods use external control points that are matched by implementing target detection methods when standard targets available or manually when targets of known coordinates can be digitized on the images[2]. The other methods are based on matching image with in the transformation space, examples of transformation used can be Fourier[2], Wavelet[13] and Wavelet Packet. Even that correlation between registered images is usually used with image registration it can be classify as an assessment tool rather than registration method. All these methods are applied with convex optimisation algorithm which aims to find the optimal registration parameters by minimizing a cost function of the applied system[14]. This optimization is based on the assumption that the accuracy level can be represented as continues complex mathematical surface form against the ranges of registration parameters. However, continuous range of registration can yield a non-convex set of accuracy levels[15]. This probability increases when higher resolution images to be used. Therefore, there are cases where automated pixel based registration cases ends to misleading local minima or even fail to converge.

This study explores a new method that implies the Monte Carlo stochastic method to feed an algorithm that uses correlation assessment as a criterion to assess all the possibilities within the registration nominal parameters ranges. The Monte Carlo stochastic method relies on repeated random sampling to map all the possible results. The samples in this case are the registration parameters. Instead of the optimisation sub-process the proposed algorithm selects the best case result as the final solution.

MATERIALS AND METHODS

Images and images pre-processing: Two types of satellite images are used in this study, Landsat 8 Images and Worldview 3 Images. Landsat is one of the most classical optical multispectral remote sensing sources for Earth observation. A great deal of research using Landsat series data has been comprised image registration for change detection, land-cover classification and image resolution merge in the content of other applications. Landsat-8 images are available with spatial resolution of 30 m. In this study three Landsat8 images were used. These images are listed in Table 1. The images were delivered as Level-1 data with 30 m spatial resolution. The level 1 processing means that the images are radio metrically corrected, orthorectifed, and georeferenced to the WGS84 coordinate system. The digital number was converted to top-of-atmosphere reflectance. The image rectification is used as the initial state for the next steps. To simulate multiresolution image registration process two of Landsat images were used with the original pixel size while the other one's pixel size are reduced to 180m as shown in Table 1.

The Worldview satellite series has received a lot of attention from the research community because it is the first released high-spectral High-Spatial resolution eight multispectral bands commercial satellite sensor. The Worldview 3 images are commercially available with 25 cm panchromatic band and 100 cm multispectral bands. A one Worldview image was used in this study, the image acquisition date was the 30th of June, 2015. The image was georeferenced and orthorectified by the provider (the Digital Globe company) and used as a reference image in this study.

Table 1: A list of landsat 8 images

Image number	Entity ID	Acquisition date	Applied pixel size
1	LC82030252014183LGN00	02-JUL-14	Original
2	LC82040252014206LGN00	25-JUL-14	Original
3	LC82040252014334LGN00	30-NOV-14	Reduced to 180 m

Proposed algorithm

Algorithm sub-processes

Mathematical processes to be used: there is a combination of expected setups for image registration input datasets. Input datasets could be either georeferenced or not. Georeferenced images could be either corrected to the terrain effect or not depending on the processing level. In all cases, scaling is required for all multiresolution images registration process as a result of the dissimilarity of pixel size and the scale accuracy as a result. Similarly, transformation is required to insure the best possible matching. Although, the rotation importance is decreased when input dataset is georeferenced especially when a long base line is used it is essential when the input dataset is not georeferenced. The proposed algorithm consider all these cases and therefore it includes scaling, transformation and rotation.

Linking features to be used: when it comes to multiresolution images registration, pixel based linking features haves more advantages comparing with object based as previously mentioned. The proposed algorithm therefore uses image subsets to make use of the geo-referencing provided by the producers of most satellite images and reduce the processing time.

Feature similarity characteristics: The correlation between the pixel values of the corresponding points is used as matching criterion for image registration. This criterion is the best available technique when images bands are spectrally overlapped. However, the spectral overlapping is important for all other pixel based criterion as well.

Alternative to optimisation: Overall mapping is used instead of optimization to overcome the problems that can occur when registration proces's accuracy behaves as a non-convex set. This alternative depends on recording the accuracy against each parameter combination and choosing the parameters that result in the maximum accuracy.

Algorithm design: The algorithm aims to achieve the registration with the minimum possible processing, regardless of the continuity and convex characteristic of the accuracy level behaviour against registration parameters range. This algorithm is designed within the context of the recently available multi-resolution pre-processed satellite imagery. The algorithm uses a number of interconnected steps to process images as shown in Fig. 1 these steps can be considered in five main stages:

The first stage includes control points selection and control image sub-images clipping: The first step in this stage is selecting control points in the overlapped area between the reference image and the input image. The number of CPs depends on the geo-referencing equation requirements, the desired accuracy level and the acceptably processing time. For example, when a polynomial equation is to be used for geo-referencing the minimum number of CPs (n) depends on the degree of the polynomial (d) with Eq. 1:

$$n = (d2+3d+2)/2 \quad (1)$$

Therefore, as higher the equation degree is as a higher number of points is required. However, the minimum number of points cannot provide an accuracy measure. In addition, more points can theoretically provide higher accuracy and lower probability of overfitting. However, the computation cost of the processing directly relates to the number of CPs. This study used 20 points with a second order polynomial (two times the minimum number of CPs). The CPs positions automatic procedure depends on creating a systematic grid of points over the overlap area. The next step is using CPs as a central point to clip subset images from both reference and input images. The subset images spatial coverage depends on the course image resolution (R). In this study a subset images of spatial coverage were equivalent to 100×100 pixel image for each Cp. The coverage (x range, y range) can be defined in terms of the CP coordinates (XCP, YCP) and the resolution (R) considered as (XCP-50R>x range>XCP+50R, YCP-50R>y range>YCP+50R).

The second stage: Includes the Monte Carlo (MC) simulation to simulate registration parameters and to apply registration for the subset images. The first step in this stage is initializing the registration parameters (the sub-image coordinates (x, y), the rotation angle(t) and the scale(s)). The initial parameters are the coordinates of the subset are the same of the original input image status. Therefore, the shifts of coordinates, rotation angles and scale are set to zeros. Then, the next step is making a random set of each registration parameter (coordinate shifts (Dx, Dy), rotation angle (Dt) and scale change (Ds). The parameters range base on the accuracy of initial state accuracy and resolutions. For level 1 processed data used in this study, the coordinate shifts, the rotation angle error and the scale change could be ±60 m (two Landsat pixels), 1° and 0.99-1.01 accordingly. The generated range distribution is set to be standard normal distribution defined by Eq. 1. This distribution insures that each parameter value chance to be included is equal to the real world probability of the same value. The other unique

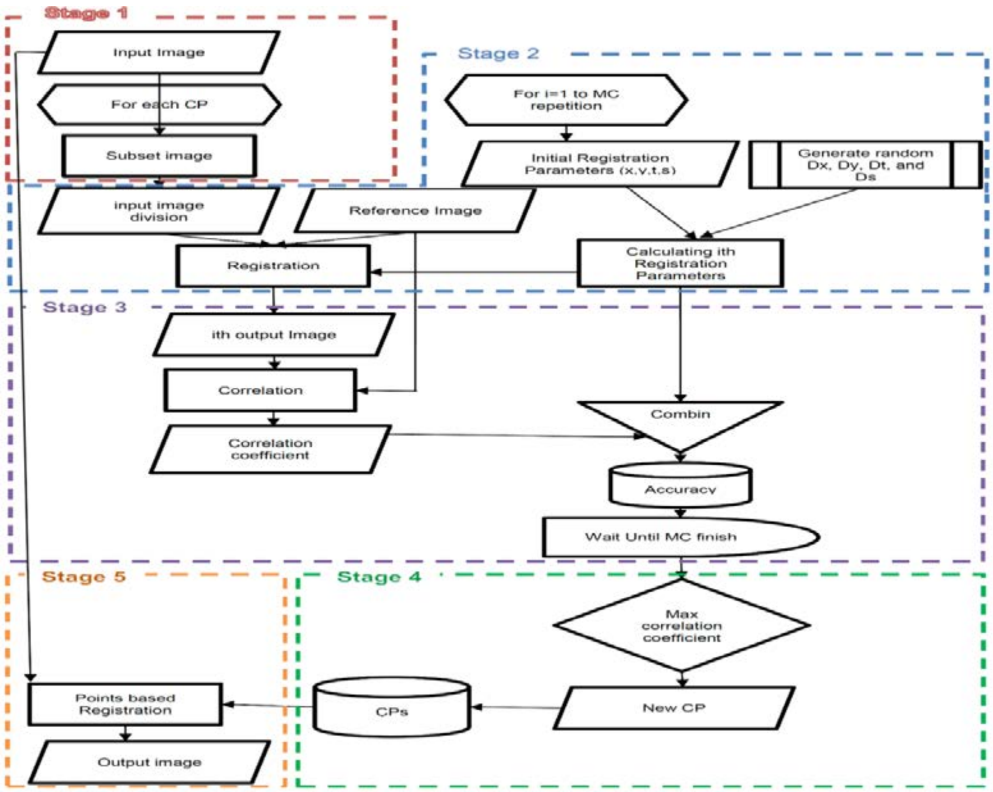

Fig. 1: A flew chart of the algorithm stages and steps

property of the normal distribution is the independence of the sample statistics estimates of the mean and variance of the distribution. The generation process includes generating random numbers and transform each random number (a) by using the procedure described by Wei *et al*.[16] and Walck[17] to convert them to a normally distributed random values. Each random set of registration parameters values is used to register the subset input image to the subset reference image.

The third stage: Includes correlating each registered subset image pixel values to the corresponding reference image pixel values. The mean of all pixels of the fine resolution image inside each pixel of the coarse resolution image is correlated to that course image's pixel. The correlation indicator is the statistical correlation coefficient (R).

The fourth stage: Includes mapping the registration parameters versus their results Rs. The registration parameters that give the highest R are used to derive a corrected control point for the next stages. The central point of each subset image is used as the new reference point to the initial input point.

The final stages: include using 90% of the corrected control point to register the whole input image. A second order polynomial transformation is used for this study. However, as long as the corrected control points are available, any other technique can be used as well. The other 10% of the control points is used as validation samples. Because these points are not used for registration, they can provide an accuracy measure by testing the correlation before and after registration.

Experimental tests

Landsat 8-to-worldview registration experiment: The first practical test is undertaken by applying the registration algorithm on the first Landsat 8 image in Table 1 as an input image and the Worldview 3 image as a reference image. The aim of this experiment is to test the correlation improvement on local and general levels. The already available level1 geo-referencing is used as initial state. The scale and the rotation angle errors are small and not effective due to the long base lines be used with satellite image geo-referencing. As a result only Dx and Dy are used as registration parameters. The red bands of both images are used. The two examples of subset images are shown in Fig. 2. In these examples the coefficients of correlations are between images with initial status are (0.60) and (0.72) while the best possible

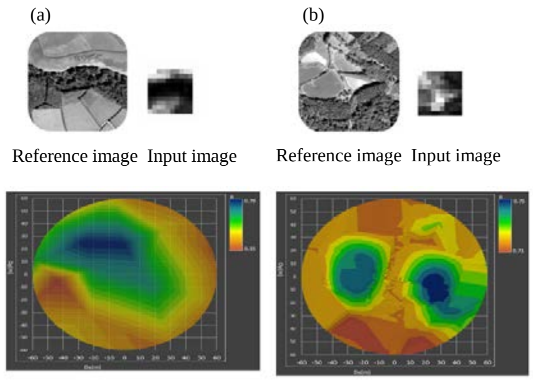

Fig. 2(a, b): Two registration results examples of Landsat8 and Worldview3 subset images. a- The correlation coefficient map as a function of Dx and Dy: map's example of one peak and b- map's example of more than one peak

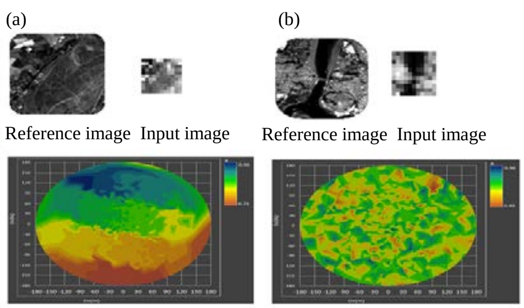

Fig. 3(a, b): Two registration results examples of Landsat 8 and reduced Landsat8 subset images. a- map's example of one peak and b- map's example of more than one peak

solutions provides Rs of 0.79, 0.75. These samples are chosen to be presented here because it shows two contrast cases. Figure 2a shows a case of one accuracy peak. About 90% of this experiments CPs are of this type. Figure 2 a shows a case example of more than one local accuracy peak. The general accuracy has improved as well; the correlation of validation samples has increased from R = 0.75 to R = 0.92.

Reduced landst8-to- original resolution landst8 registration experiment: The other experiment is implemented to assess the spatial accuracy rather than the correlation. Therefore, a datasets of the same sensor (Landsat 8) are used. This way, it will be guaranteed that both datasets have the same geo-referencing inputs and were processed in the same way and can be dealt with as reference data. To simulate the multi-resolution cases, one of the images spatial resolution were reduced from 30m to 180m. This image is deliberately shifted image with small distances in x and y directions to test the ability of the algorithm to reverse this shifting. The red bands of both images are used. The results show a root mean square error of ±18m. The examples shown in Fig. 3 illustrate results of two sub-images. The first case represents a case of an accuracy map that has one peak (Fig. 3a). About 80% of control points are similar to this case. While the second one represents a result of a fluctuated accuracy against the change in the registration parameters that has more than one local peak.

RESULTS AND DISCUSSION

In this study, we have presented a new algorithm of image registration based on stochastic representation of all possible situations. The implemented statistical method to provide the stochastic range of inputs, provide there results, map the accuracy and select the best results is Monte Carlo method. We also carried out two experiments to test the algorithm. This algorithm can only applied with an initial registration parameters with accuracy level that can guarantee intersection between input and reference subset when the range of registration parameters is applied. This condition is provided under the proposed framework to apply this algorithm is the provided geo-referenced satellite images. It can be used to improve the results of other registration methods for other applications. However, its ability to deal with other contexts has not been tested here. The time expense of this method has not been tested. Nevertheless, it is expected to be high compared to other methods due to the basic concept of Monte Carlo method. However, the number of Monte Carlo iterations is directly related to the time consuming and computation expenses. The other important factor for time cost is the subset image's size and the resolution variation between the input and reference images. We have chosen to analyse our results principally by measuring both correlation and spatial registration accuracy. More future assessment can be taken place in the future works to test this algorithm with deferent image types and for different applications.

CONCLUSION

In this research, we demonstrate an algorithm for image registration that can find the best possible accuracy unrelatedly to the resolution differences between the input and output images. The main advantage of this method is that it does not set any assumption to the accuracy behaviour (continuity and convex characteristic) against the variation of the registration parameters.

The proposed algorithm based on Monte Carlo method to provide all possible ranges of scales, rotation angles, and shifting distances in x and y directions. The algorithm uses image subsets and applies a pixel based correlation between input and reference images. Also, it uses overall mapping as an alternative to the optimization to overcome the problems of optimization divergence cases.

The algorithm mechanism includes extracting sample subsets, applying Monte Carlo method to find the registration of the best correlation results for each subset, redefine the CPs and using the redefined CPs to register the main images to each other's. However, this algorithm cannot be applied without acceptable initial setting for the registration parameters.

When the algorithm applied on Landsat8 and Worldview3 images, the accuracy maps results shows that 10% of the subset images can be problematic with conventional methods. The validation results of this experiment show a significant improvement in the correlation coefficients from $R = 0.75$ to $R = 0.92$. When it was applied on Landsat8 original images and reduced images, the results shows that about 20% of the cases can be problematic with conventional methods because does not match the assumption of the optimization schemes. The spatial accuracy test yield in RMSE of ±18 m that is relatively small compared to ±30 m (one Landsat 8's pixel) best scenario visual registration error.

These promising results suggest that this algorithm can be applied with the context of level1 Landsat and Worldview satellite images and similar data. A further testing is required to test this algorithm with deferent types of images, compare it to other methods in terms of costs and relative accuracy improvement.

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