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Accurate point matching based on multi-objective Genetic Algorithm for multi-sensor satellite imagery

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ABSTRACT

This paper investigates a novel approach for point matching of multi-sensor satellite imagery. The feature (corner) points extracted using an improved version of the Harris Corner Detector (HCD) is matched using multi-objective optimization based on a Genetic Algorithm (GA). An objective switching approach to optimization that incorporates an angle criterion, distance condition and point matching condition in the multi-objective fitness function is applied to match corresponding corner-points between the reference image and the sensed image. The matched points obtained in this way are used to align the sensed image with a reference image by applying an affine transformation. From the results obtained, the performance of the image registration is evaluated and compared with existing methods, namely Nearest Neighbor–Random SAmple Consensus (NN–RanSAC) and multi-objective Discrete Particle Swarm Optimization (DPSO). From the performed experiments it can be concluded that the proposed approach is an accurate method for registration of multi-sensor satellite imagery.

1. Introduction

Image registration is the process of geometrically aligning two images in a way that corresponding pixels in the two images correspond to the same physical region of the scene being imaged [1–4]. The images may be taken at different times, with different sensors and from different viewpoints. The image to be aligned is called the *sensed* (or input) *image*. The image with respect to which the alignment is carried out is called the *reference* (or base) *image* and the transformed sensed image is called the *registered image*.

Some of the challenges encountered in multi-sensor image registration include: (i) differences in intensity and contrast of corresponding regions captured by different sensors; (ii) differences in scale that lead to multiple intensity values in one image mapping to a single intensity value in another image; (iii) the common physical region between two images may be small and prominent structures may be present outside of the common region [5,6].

Image registration methods are classified into two broad categories, namely *area-based methods* and *feature-based methods*. Area-based methods operate under the assumption that a strong relationship exists between intensities of the images to be registered. They attempt to match intensity values by using mutual information, correlation or other

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probabilistic information. These methods often lead to a poor registration performance, especially with a great variation of contrast and brightness between images [7,8].

Feature-based methods find the similarity between images based on high level features such as edges, contours and corners. This generally makes them more robust to intensity variations, relatively small common information regions and sensor noise, which are some of the major issues that arise in multi-sensor image registration. Also, the data in the form of feature-points that can be explained by the hypothetical model are called inliers of this model. The other points, generated by matching errors are called outliers. There are several methods for identifying feature-points as inliers or outliers. Traditionally, RanSAC estimation method introduced by Fischer et al. [9] is widely applied. Here, a set of points is picked from the reference image and the sensed image and the transformation between them is computed. This transformation is applied to the remaining set of points and the number of inliers is computed. If this number is found to be above an empirical threshold, it is considered a good match. The method also tends to map a correspondence between outliers as it performs matching only based on homography and Euclidean distance. To tackle this, various variants of RanSAC have been proposed.

Torr et al. [10] used Maximum Likelihood Estimation SAmple Consensus (MLESAC) for estimating the image geometry by sampling points based on the likelihood of their belonging in the solution set. The same technique has been extended to Maximum A Posteriori SAmple Consensus (MAPSAC) [11] which takes posterior probability into account. However, this fails when the prior information about the sampling points is insignificant. Chum et al. [12] successfully applied PROSAC (PROgressive SAmple Consensus) on the wide-baseline matching problem. In their study, to improve computational efficiency, they exploited the linear ordering defined on the set of correspondences using a similarity measure, instead of random guesses.

Further, various population-based methods (metaheuristic methods) [13–16] are used to improve RanSAC with a heuristic search optimization technique. Chai et al. [17] applied a modified genetic operator to incorporate the epipolar geometry constraint into the matching process. Saito et al. [18] used Genetic Algorithm in the stereo image matching. Also, Particle Swarm Optimization [19] has also been used as an improvement over RanSAC for determining a correspondence between sensor images [20]. Recently, multi-objective Discrete Particle Swarm Optimization (DPSO) has been developed in order to match multi-sensor images [3,6]. A population-based method called GASAC [21–23], which uses a Genetic Algorithm (GA) [24] in combination with RanSAC, has found to yield better results than RanSAC.

In this paper, we propose an algorithm to match corresponding points in the reference and sensed images using a multi-objective function. This objective function combines the angle and distance to successfully eliminate any incidental correspondence between outliers. An additional parameter to select transformations with the number of matching corner-points being greater than a set threshold is included in the evaluation of fitness. This is similar to the matching criterion of the RanSAC algorithm. Objective switching is also used to select among the different genetic operators to ensure continual replenishment of the active population of feature-points while retaining the good matches until a desired fitness index for the entire population of feature-point sets is achieved. The method is evaluated in experiments using different quality measures [23]. The performance is compared to traditional methods such as the Nearest Neighbor–Random SAmple Consensus (NN–RanSAC) [25] and the multi-objective DPSO [6] population-based method for matching multi-sensor satellite images. The experimental results obtained indicate that the proposed approach is more accurate in matching multi-sensor images.

The paper is organized into the following sections. Section 2 contains the problem formulation and problem definition. Section 3 describes the methodology used. Section 4 and 5 explains the performance measures and results obtained on various multi-sensor image sets. We conclude the paper in Section 6 by summarizing the observations.

2. Problem formulation

Multi-sensor imagery cannot always be matched accurately by only using spatial distances in the feature space to determine fitness. Hence the fitness function is evaluated as a combination of three measures for better matching of corner-points in the reference and sensed images. Multi-sensor satellite imagery can be registered using the affine transformation [26] which takes into account scaling, rotation, translation and shearing effects. A set of three matched points is necessary to compute the transformation to be applied to the sensed image to obtain the final registered image.

The components of the fitness function is explained using a general (reference or sensed) image with corner-points I, J and K as shown in Fig. 1. Let the I, J, and K be three corner-points (features) detected in the reference image and let P, Q, and R are three corner-points (features) detected in the sensed image. The problem is to match these points I, J, and K to one of the points of P, Q and R. Hence, there are 6 possible combinations for this matching problem. They are: (P,Q,R), (P,R,Q), (Q,P,R), (Q,R,P), (R,P,Q) and (R,Q,P). For example (Q,R,P) means that point I is matched to Q, J is matched to R, and K is matched to P. We need to find the best match out of these possible combinations. In order to find the best matching, we use the objectives namely angle criterion, distance condition, and point matching condition. The angle, distance, and point matching condition are explained below:

2.1. Angle criterion

The angle criterion aims to select points for which the cumulative error between corresponding angles of a triangle formed by the points in the reference image and the sensed image attains a value within permissible error limits.