Multi-objective optimization of satellite image registration using discrete particle swarm optimisation

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***Abstract*—A new multi-sensor image registration technique is proposed based on detecting the feature corner points using modified Harris Corner Detector (HDC). These feature points are matched using multi-objective optimization (distance condition and angle criterion) based on Discrete Particle Swarm Optimization (DPSO). This optimization process is more efficient as it considers both the distance and angle criteria to incorporate multi-objective switching in the fitness function. This optimization process helps in picking up three corresponding corner points detected in the sensed and base image and thereby using the affine transformation, the sensed image is aligned with the base image. Further, the results show that the new approach can provide a new dimension in solving multi-sensor image registration problems. From the obtained results, the performance of image registration is evaluated and is concluded that the proposed approach is efficient.**

Keywords – Multi-sensor image, Modified Harris Corner Detection, Discrete Particle Swarm Optimization.

I. INTRODUCTION

Image registration [1] is the process of aligning the image obtained from either different sensor, at different times, different viewpoint with the reference image. The image on which the registration process is done is called the base or the reference image and the image which is registered is known as the sensed image.

Basically image registration process involves two types such as area based registration [2] and feature based registration [3]. Area based registration is based on detecting the overlapping region(s) in the base and sensed image using correlation, mutual information, standard deviation and other probabilistic or statistical tool applied on an area or a region of interest [2]. The latter method of feature based registration deals with detecting features - corners, edges and contours in both sensed and base image and thereafter finding the match between the features obtained in the two images [3]. Further, transformation is obtained for the sensed image using the matched features.

Image Registration has varied application for multi-temporal and multi-sensor images such as remote sensing and medical imaging for object recognition and feature extraction.

Many researchers have observed matching features as NP Hard problem. Hence, there doesn't exist any robust method for registering multi-temporal and multi-sensor images in the literature [1]. Earlier feature matching was done manually which was intensive and was subjected to human error and bias [2]. Additionally, some semi-automatic methods based on angle had been used for matching points [4]. To overcome this, traditionally RanSAC [5] was used to match points automatically by classifying the points detected into inliers and outliers [6, 7]. However in several instances it was observed that RanSAC picks point from the outliers [6]. Therefore, a more efficient method was then proposed by incorporating population based method such as Genetic Algorithm (GA) [7] and Particle Swarm Optimization (PSO) [6] along with RanSAC to find the best match.

Contribution to this paper: In earlier study, Discrete Particle Swarm Optimization (DPSO) with RanSAC had been used for registering same sensor images with distance as the sole fitness function. In this study, a new approach is proposed based on modified Harris Corner Detection (HDC) for detecting the feature points and optimizing the match using DPSO based on multi-objective functions - distance and angle. The fitness functions are evaluated using objective switching method. Further the performance of image registration is evaluated using quality measures.

II. PROBLEM FORMULATION

For registration of multi-sensor images, only distance as the fitness function is not sufficient as the images are of different scales. Hence for accurate registration of such images, better matching is obtained by including angle as fitness criterion beside distance.

Let U and V represent the set of corner points detected in base and input image [4].

$$U = \{a_1, a_2, a_3, \ldots, a_i, \ldots, a_m\} \qquad 1 \le i \le m$$
$$V = \{b_1, b_2, b_3, \ldots, b_j, \ldots, b_n\} \qquad 1 \le j \le n$$

where the co-ordinate of point a_i and b_j is given by (x_{ai}, y_{ai}) and (x_{bj}, y_{bj}) in their respective co-ordinate system.

For applying affine transformation, feature matching is to be obtained for three corresponding points in base and sensed image. Hence, the points considered for feature matching in base image be a_i, a_j and a_k and in input image be b_i, b_j and b_k.

A. Distance Condition

The distance between two points' p and q is given in Eq. 1.

$$D=||p-q|| \quad (1)$$

For the base image, the length between points a_i and a_j is calculated using Eqn. 1 and designated by l^a_{ij}. Similarly for the sensed image the length between points b_i and b_j is denoted by l^b_{ij}. Likewise other distances in the base and sensed are calculated and denoted as l^a_{jk} and l^b_{jk}.

Using the distances obtained above, ratios R_{ij} and R_{jk} are calculated as shown below.

$$R_{ij}=\frac{l^a_{ij}}{l^b_{ij}} \quad (2)$$

$$R_{jk}=\frac{l^a_{jk}}{l^b_{jk}} \quad (3)$$

$$\delta_l=|R_{ij}-R_{jk}|,\ 0<\delta_l<t_1 \quad (4)$$

If the absolute difference of ratios R_{ij} and R_{jk} is within the threshold limit t_1 then the base and input points are selected.

The constraints involved here is that the above difference in the ratio should be less than the threshold 't_1' set. Secondly, only three points are involved in checking the distance condition.

However for multi-sensor images, feature matching can be done more efficiently by using angle [4] as another fitness function.

B. Angle Criterion

Angle criterion [4] refers to the minimization of the difference in the corresponding angles measured in the base points and the input points chosen from the base and sensed image respectively.

Let the slope between two points be denoted as:

$$m_{ij}=\frac{y_j-y_i}{x_j-x_i} \quad (5)$$

Using Eqn. 5, slope of the line joining a_i and a_j in the base image is calculated and denoted as m^a_{ij}. Similarly m^a_{jk} is also calculated. Likewise, for the sensed image, slope of the line joining b_i and b_j is given by m^b_{ij} .In the similar manner, m^b_{jk} is obtained. Now the angle enclosed at point a_j in base image is given by:

$$\theta_j=\frac{m^a_{ij}-m^a_{jk}}{1+m^a_{ij}*m^a_{jk}} \quad (6)$$

Similarly the angle enclosed at b_j in sensed image is

$$\varphi_j=\frac{m^b_{ij}-m^b_{jk}}{1+m^b_{ij}*m^b_{jk}} \quad (7)$$

If the points are corrected picked

$$\delta_\theta=|\theta_i-\varphi_i|,\quad 0<\delta_\theta<t_\theta \quad (8)$$

The constraints involved here in this criterion are as follows. Firstly, the difference in the corresponding angles should be less than the threshold t_θ set as referred in Eqn. 8. Secondly, only the angles of the three corresponding points are considered here.

C. Multi-objective Optimization

Given a n-dimensional variable vector, $X=\{x_1,x_2,\ldots,x_n\}$, the main objective is to find a X which minimizes/ maximizes a given set of K objective functions $obj(X)=\{obj_1(X), obj_2(X),\ldots, obj_K(X)\}$. The solution is restricted to a number of constraints $f_j(X)\leq b_j$ where b_j is the search space of the variables.

In many cases, objective functions taken into consideration conflict with each other [8]. For instance, optimizing x with respect to one objective function may not optimize some other objective function. In reality as it is impossible to minimize each objective function, hence it is easier to find X such that it satisfies all the objective functions at an acceptable limit without any domination of any objective function over the other.

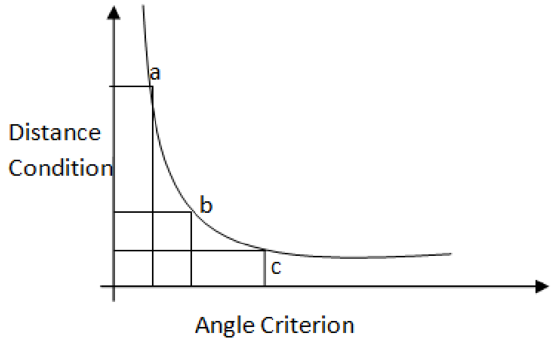

Fig. 1: Conflicts in Multi-objective Optimization

The above graph illustrates the nature of the conflicts in any optimization process. In this study, distance represents one objective function and angle represents another objective function. Both of them are subject to minimization. In Fig. 1, point 'a' is a point where distance condition is violated while angle criterion is satisfied, 'c' is where angle condition is violated whereas distance condition is satisfied and point 'b' represents a location where both the objective functions are minimum. This leads to the finding of pareto optimal solution. The ultimate goal is to find the best pareto optimal solution since it is virtually impossible to obtain the entire pareto optimal solution for very large arrays like the corner points obtained in base and sensed image in this case

III. METHODOLOGY

A. Point detection by Harris Corner Detector

Due to invariance to noise, illumination and affine parameters, Harris Corner Detector (HDC) is considered superior to precedent method proposed by Moravec [9]. Here it calculates the gradient co-variance in the intensity level at a point given the shifts in X and Y axis. Thus by evaluating the change in the intensity along X and Y axis at point we arrive at the following expression for the gradient co-variance matrix [9]:

$$G=\begin{bmatrix}\sum_W I_x^2 & \sum_W I_xI_y \\ \sum_W I_xI_y & \sum_W I_y^2\end{bmatrix} \quad (9)$$

where I_x and I_y are the gradient of the intensities along X and Y direction.

If the response of the above matrix at a point is above the threshold assigned then the point is classified as a corner. The response R is given in Eq. 10.

$$R=det(G)-.04*trace(G) \quad (10)$$

Schmid et al. [10] analyzed and compared different corner detector method and concluded HDC performs better. In literature, there exist several other corner detection schemes such as KLT, Susan, Kitchen-Rosenfeld etc.. The performance of KLT and Harris [11] is better than the aforementioned schemes. Bentoutou et al. [12] applied successfully modified version of the HDC to register multi-sensor image. In this study, control points of modified HDC are used to register multi-sensor image.

B. *Discrete Particle Swarm Optimization*

RANSAC uses a single point for point correspondence while DPSO treats the cluster of base points and its corresponding input points as discrete entities of non-repeating whole number stored in the position vector (X_i). This has an associated fitness value to indicate its correspondence. Furthermore, each particle vector has a previous best value in terms of the fitness value associated with its previous best vector (B_i). Each previous best vector of a particle infers about the most optimal match of those corresponding base and input points that is represented by discrete non-repeating integers in the previous best vector. There exists a global best vector G which has the best fitness value.

For updating the attributes of a particle, new attributes are obtained using velocity vector which is initially defined as [13]:

$$V(i)=\begin{bmatrix} 1 & 1 & 1 & \ldots\ldots & 1 \\ 1 & 2 & 3 & \ldots\ldots & N \end{bmatrix} \quad (11)$$

where the first row is the proportional likelihood associated with the corresponding attribute present below for a particle and the second row indicates the attribute.

Further by using positional weights α, β and γ, the new proportional likelihood is obtained by increasing it by α if attribute is present in X_i, β if the corresponding attribute is present in B_i and γ for G [13].

Therefore we obtain the new velocity vector as:

$$V(i)=\begin{bmatrix} w_1 & w_2 & \ldots\ldots. & w_n \\ 1 & 2 & \ldots\ldots. & N \end{bmatrix} \quad (12)$$

where $w_j=1+\alpha*\delta(\alpha)+\beta*\delta(\beta)+\gamma*\delta(\gamma)$

$$\delta(\alpha)=\begin{cases} 1 \text{ if } v(2,j) \in X(i) \\ 0 \text{ if } v(2,j) \notin X(i) \end{cases}$$

$$\delta(\beta)=\begin{cases} 1 \text{ if } v(2,j) \in B(i) \\ 0 \text{ if } v(2,j) \notin B(i) \end{cases}$$

$$\delta(\gamma)=\begin{cases} 1 \text{ if } v(2,j) \in G \\ 0 \text{ if } v(2,j) \notin G \end{cases}$$

Finally the columns are ranked in the decreasing order of the likelihoods. The first three new attributes are chosen for the particle vector and its fitness value is computed and compared with fitness value of the global best particle and previous best of the particle. The corresponding particle best vector and global best vector is updated on obtaining a better fitness value.

IV. RESULTS AND DISCUSSIONS

In this section, first the two corner detection techniques viz. modified HDC and KLT are compared on a synthetic image. To illustrate the working of the proposed method to match points, it is applied on two synthetic images and one real time image. The performance of the method is evaluated using Mutual Information (MI) and Root Mean Square Error (RMSE).

MI measures the mutual dependence of two variables involved. If MI is more, then the image is well registered. RMSE is used to compute error in the intensities of the corresponding points in the registered image and the ground truth image. If RMSE value is closed to 0, then registration process is better.

Fig. 2 and Fig. 3 show the corners obtained from modified HDC and KLT for the synthetic base image.

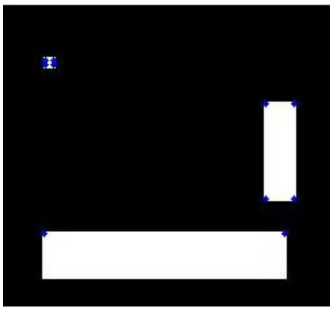

Fig. 2: Corners from modified HDC

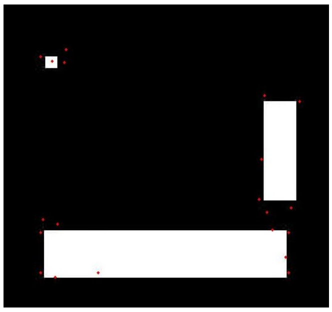

Fig. 3: Corners from KLT

By calculating the RMSE of the corner displacements for the above image, it was noted that in case of modified HDC, the average corner shift is 3 pixels whereas it was around 12 pixels for KLT. Hence modified HDC was opted for corner detection scheme. Fig. 4 and Fig. 5 show the base and the sensed synthetic image.

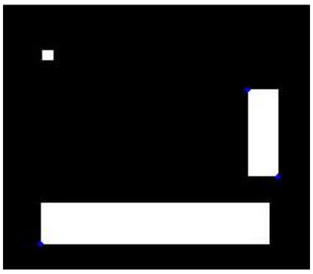

Fig.4: Reference Synthetic Image

Fig. 5: Sensed Synthetic Image

The corner points obtained are then subjected to optimization using DPSO incorporating the multi-objective fitness function. The fitness value of both distance and angle in this case is 0. Finally after getting the registered image as shown in Fig.6, the registered image is compared with the ground truth image and the performance of the approach is tabulated in TABLE 1. The mutual information of the unregistered image with the base image is .0173.

TABLE I. PERFORMANCE MEASURE

MI	RMSE
.8745	.0348

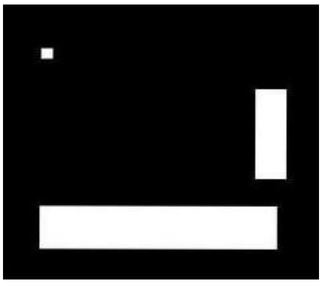

Fig. 6: Registered Image

The optimization through multi-objective fitness function incorporated DPSO is robust as it is able to register the image independent of which scheme is applied for corner detection provided the corner detection is appropriate. To match the points, this method was found to be better than standard RANSAC for different runs.

This method is tested with the synthetic image, where sensed image (Fig. 8) is sheared version of reference image (Fig. 7). In this case also the sensed image is aligned according to reference image as shown in Fig. 9. Hence, the robustness is shown by studying another set of synthetic images.

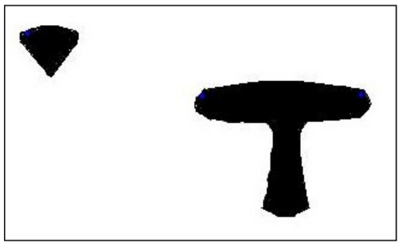

Fig. 7: Reference Image

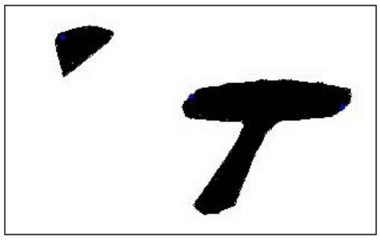

Fig. 8: Sensed Image

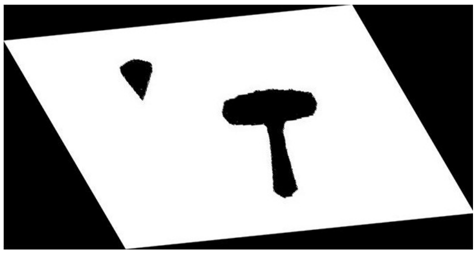

Fig. 9: Registered Image

Further this method is implemented on a real time image. The multi-sensor image used here are QuickBird multi-spectral image (2.4 m resolution) and QuickBird panchromatic image (0.6 m resolution) covering the scene of Bangalore, Karnataka, India. Fig. 10 is QuickBird multi-spectral image which is used as base image and Fig. 11 is QuickBird panchromatic image used as the sensed image. Fig 12 is the final overlaid image of the registered image with the base image. Using modified HDC, 40 corner points were detected in the base image and 62 points were detected in the sensed image. TABLE 2 evaluates the performance of the method for the real time image used when compared to ground truth.

Fig. 10: Reference Image

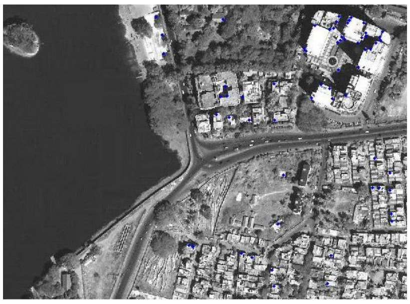

Fig. 11: Sensed Image

Fig. 12: Registered Image

TABLE II PERFORMANCE MEASURE OF REAL TIME IMAGE

MI	RMSE
1.5813	.2465

The MI value of the unregistered image with the base image in the above case is 0.8832. From TABLE 2, we can observe that for the registered image the MI value is 1.5813 which is more than unregistered image. Hence it shows that the DPSO using multi-objective optimization functions picks better matched points between the sensed image and the base image.

V. CONCLUSION

In this paper, a new approach to multi-sensor image registration is proposed. By using distance and angle as multi-objective fitness function in the optimization process using DPSO, the proposed method is able to register the sensed image with the base image by incorporating matched corners obtained from modified HDC. From the results, we can observe that the new approach is efficient for multi-sensor satellite image registration.

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