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Present Scenario In Automatic Image Registration Methods

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ABSTRACT: *Image registration is a crucial step in most of the image processing tasks. Traditional techniques such as area and feature based methods have several limitations. A fully automatic image registration approach which is accurate, fast, and robust is required. This paper discuss on the recent innovative integration methods such as Integrated SMI and Integrated SIFT&MI that will overcome the respective weaknesses of registration accuracy and computational load. The methods have been tested by using several images acquired from different sensors. The experimental results shows that the above methods are highly accurate and more robust than the conventional metrics.*

Keywords- *ACO_{R},, affine transformation, Automatic image registration, Descriptors, Key points, MI, Phase congruency model, scale space, SIFT, SMI.*

I. INTRODUCTION

During the last decades, the rapid development of image acquisition devices and digital techniques resulted in generation of diverse set of raster images. The requirement of processing these images invoked the research and advances in image processing. Automatic image registration is one of the crucial step in image processing. It can be defined as the process of determining the transform which geometrically aligns the two different images, reference image and sensed image, of the same scene acquired at different times, from different viewing angles and/or by different sensors. The differences in images can be due to the changes in the scene or the varying imaging conditions. Automatic image registration will transform different sets of data into one coordinate system. The comparison and integration of data obtained from different measurements necessarily requires image registration.

Traditional image-registration techniques required the manual selection of ground control points (GCPs) at significant landmarks of the images. These GCPs are then used to estimate the transformation model that aligns one image to another. The primary drawback of this approach is that, a trained expert is needed for selecting each individual GCP manually in the remotely sensed images. While dealing with raster images that are available today this process is very laborious and time consuming. Therefore, an automatic method for aligning such images is highly desired. Image registration has been widely used in many fields such as computer vision, medical image analysis, cartography, pattern matching, and remote sensing image processing [1].

As the name implies automatic image registration methods will automatically choose registration elements which are more appropriate for images under processing. A number of methods have been proposed to automate the process of image registration that can be generalized into four categories:

1) Pixel intensity based methods: Also known as area based methods. In these methods alignment between images can be determined by using similarity measure between pixel intensities. Similarity measures used in these algorithms include maximum likelihood, mutual information and correlation.

2) Methods based on frequency-domain characteristics: Frequency domain characteristics of two images is used to find optimal alignment between images.

3) Low level feature based methods: The low level features such as edges, corners and ridges are extracted from the two images and correlation between these features is used to determine the optimal alignment between the images. Such methods are useful in images which are distorted but consists of distinctive features.

4) High level feature based methods: In these methods high level features such as regions and specific objects are extracted from images. Descriptors of these features are then used to determine the optimal alignment between images. But the above mentioned methods have disadvantage of poor registration accuracy and computational load. Thus mainly there are three characteristics that should be considered in the design of any automatic image registration system [1-2].

1) Efficiency: It is the ability to align raster images with minimum computational effort while maintaining registration accuracy.

2) Robustness: The effect of image variances due to factors such as environmental noise, differences in illumination and contrast etc. should not influence accuracy.
3) Accuracy: a registration accuracy of less than 0.2 of a pixel is demanded to achieve a change detection error of less than 10% [3].

Therefore in order to meet the specifications as discussed above, the present automatic image registration methods are focusing on integration of area based and feature based methods. This paper is intended to discuss various integration methods that will overcome the weaknesses of registration accuracy and computational load, of the existing practical image registration methods. The recent efficient integration methods are, Integrated SMI and Integrated SIFT&MI.

The rest of the paper is organized as follows. Section II describes the Integrated SIFT & MI in detail. Section III includes a detailed description of Integrated SMI metric. Section III gives experiment results and related analysis. Section IV concludes the whole paper.

II. INTEGRATED SIFT & MI METHOD

This algorithm consists of two phases. The primary phase includes performing SIFT and modified outlier removal procedure, which eliminates most of the false mismatches and the result is close to ground value. Secondary phase will consider MI for more accurate results. SIFT, scale invariant feature transform is capable of extracting distinctive invariant features from grey level images. It can be applied to images which are present with rotation and scale changes, change in viewpoint, addition of noise, rescaling, in-plane rotation and changes in illumination. But the problem associated with SIFT is that, the number of the detected feature matches may be small. As mentioned earlier MI, mutual information is one of the area based method which represents a measure of statistical dependence between two images. MI is more robust to noise and produces consistently sharper peaks at the correct registration values than correlation, but MI has a limitation in the need of predefined parameter range [4]. The block diagram of the proposed method is shown in figure1.

2.1 Scale invariant feature transform (SIFT*):* Scale Invariant Feature Transform (SIFT) is an algorithm for detecting and extracting local feature descriptors for key-points that are reasonably invariant to changes in illumination, rotation, scale, noise, and small changes in viewpoint [5]. It was first proposed in [6]. The features are well localized in both the spatial and frequency domains. In addition, highly distinctive features allows a single feature to be correctly matched with high probability against a large database of features, providing a fundamental basis for object and scene recognition. The major stages of computation used to generate the set of image features are:
1) Scale-space extrema detection
2) Keypoint localization
3) Orientation assignment
4) Generation of keypoint descriptors.
1) The first stage of key point detection is to identify locations and scales that can be repeatedly assigned under differing views of the same object. It requires a multi-scale approach for detecting locations that are invariant to scale. This continuous function of scale known as scale space. The only possible and feasible scale-space kernel is the Gaussian function. Let $L(x, y, \sigma)$, is the scale space of an image which is produced from the convolution of input image, $I(x, y)$ with variable-scale Gaussian, $G(x, y, \sigma)$:
:

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma). \end{aligned} \tag{1}$$

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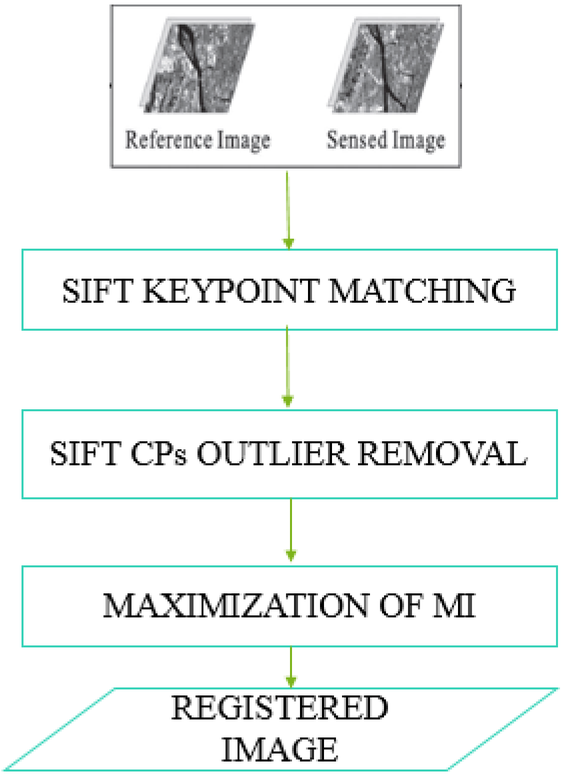

Fig 1 Block diagram

The keypoints are the extrema of the DoG functions, i.e. they are maximum or minimum peaks of the function.
2) Accurate keypoint localization: The location of the extrema is refined by considering a parabolic fit. Two filters are used to discard the keypoints with small contrast and the edges, that are not discriminative for the image.
3) Orientation assignment :By assigning a consistent orientation to each key point, the key point descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation.
4) The local image descriptor: Each descriptor contains an array of 4 histograms around the key point and each histograms contain 8 bins. This leads to a SIFT feature vector with 4 * 4 * 8 = 128 elements. Normalizing this vector will enhance invariance to changes in illumination.
5) Sift feature matching: The main steps include Find nearest neighbour in a database of SIFT features from training images. For robustness, use ratio of nearest neighbour to ratio of second nearest neighbour. Neighbour with minimum Euclidean distance which is very expensive search. Use an approximate, fast method to find nearest neighbour with high probability.
6) Recognition using sift features: Compute SIFT features on the input image. Match these computed features to the SIFT feature database. Each key point specifies 3 parameters: scale ,2D location, and orientation. To increase recognition robustness: Hough transform is used to identify clusters of matches that vote for the same object pose.
7) Modified outlier removal: A reliable outlier removal process is necessary for the removal of false initial matches. Given two sets of m matched key points {Ri} and {Si} belonging to the reference and sensed images, respectively, let RiRj be the distance between key points Ri and Rj , and SiSj be the distance between key points Si and Sj. A distance ratio Dij is defined as:

$$Dij = RiRj / SiSj \qquad (2)$$

Ratios of Dij are computed based on all $m(m - 1)/2$ possible combinations, and the number of Dij in the intervals is counted in a statistical way, forming a scale histogram. The denser cluster in the scale histogram corresponds to the true scale difference between the images. The key point pairs that contribute to the cluster are accepted as correct matches, while the ones that are scattered and away from the cluster are considered as incorrect matches and are then eliminated [6].

2.2 Mutual information: A joint histogram of two images can be used to estimate a joint probability distribution of their grey values by dividing each entry in the histogram by the total number of entries. The Shannon entropy for a joint distribution is defined as:

$$H(A,B) = -\sum_{I,j} p(I,j) \log p(i,j) \tag{3}$$

By finding the transformation that minimizes their joint entropy, images should be registered. Once entropy, a measure from information theory, had been introduced for the registration of multimodality medical images, another such measure quickly appeared which is known as mutual information. For two images A and ***B***, mutual information I can be defined as:

$$I(A,B) = H(B) - H(B/A) \tag{4}$$

Where H(B) is the Shannon entropy of image B, computed on the probability distribution of the grey values. H(B |A) denotes the conditional entropy. When interpreting entropy as a measure of uncertainty, the amount of uncertainty about image B minus the uncertainty about B when A is known. In other words, mutual information is the amount by which the uncertainty about B decreases when A is given: the amount of information A contains about B. Because A and B can be interchanged, I(A,B) is also the amount of information B contains about A. Hence, it is mutual information. Registration is assumed to correspond to maximizing mutual information: the images have to be aligned in such a manner that the amount of informationthey contain about each other is maximal [7]. The second form of definition is most closely related to joint entropy.:

$$I(A,B) = H(A) + H(B) - H(A,B). \tag{5}$$

This form contains the term $-H(A,B)$, which means that maximizing mutual information is related to minimizing joint entropy. We have described above how the joint histogram of two images' grey values disperses with misregistration and that joint entropy is a measure of dispersion. The advantage of mutual information over joint entropy is that it includes the entropies of the separate images.The joint probability distribution p(a, b) is then estimated by :

$$p(a, b) = \frac{h(a,b)}{n} \tag{6}$$

normalized measure of mutual information is given by:

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)} . \tag{7}$$

NMI(A,B) is defined as a measure of information redundancy between two images, the value of MI is maximal when the two images are geometrically aligned [8].

2.3 Modified marquardt–levenberg search strategy: An optimizer that converges in a few criterion evaluations when initialized with good starting conditions is always desired. A specifically designed optimizer exhibits super linear convergence when close enough to the optimum [4]. It is a modification of the traditional Marquardt–Levenberg and can be described by:

$$\boldsymbol{\mu}(k+1) = \boldsymbol{\mu}(k) -(HS(\boldsymbol{\mu}(k))^{-1} * \nabla S (\boldsymbol{\mu}(k)) \tag{8}$$

Where ∇S and HS are the gradient and the modified Hessian of MI, respectively. The gradient ∇S is defined as

$$\nabla S = [\frac{\delta S}{\delta \mu 1} \quad \frac{\delta S}{\delta \mu 2} \quad ....] \tag{9}$$

The modified Hessian HS is defined as

$$[HS(\boldsymbol{\mu})]i,j = [\nabla^2 S(\boldsymbol{\mu})] i,j * (1 + \delta_{i,j}\lambda) \tag{10}$$

Where $\delta_{i,j}$ is the Kronecker symbol, λ is a tuning factor, and $\nabla^2 S$ is the Hessian of S. $\nabla^2 S$ is defined as the matrix of the second derivative of S .

III. INTEGRATED SMI METRIC

The basic principle of these methods is to find the optimal transformation parameters in such a way that the similarity metric will be maximized or minimized. It can be expressed as:

$$\alpha* = \arg \text{opt} (S (A, T\alpha(B))) \tag{11}$$

The SMI metric can be represented as a function of SI and MI:

$$SMI(T\alpha) = SIA,B \bullet MIA,B. \tag{12}$$

Where A and B are the images to be registered, Tα is the affine transformation model, α is the transformation parameters such as rotation, scale, etc. and S represents the similarity metric. Here SIA,B represents the spatial information of the reference image A and the sensed image B, MIA,B represents the mutual information. Both of them are functions with respect to the transformation parameters:

$$SIA,B=SI (A, T\alpha(B)) \tag{13}$$

$$MIA,B=MI (A, T\alpha(B)) \tag{14}$$

A similarity measure SMI is considered a metric if it produces a higher value as the dependency between corresponding values in the sequences increases. That is only when both of the above two terms are large, then the SMI will reach its maximum [8].

3.1 Spatial Information (SI):Spatial Information describes the physical location of objects and the metric relationships between objects [2]. The SI of SMI is used to efficiently estimate near global-optimal transformation and correct the predefined parameter range of MI. The phase congruency model [9] is used to extract similar distributed features from multisensor images. In the proposed method, the modified Hausdorff distance is used to measure the spatial relations of the extracted features. Phase congruency operator uses the principal moments of the phase congruency information to determine corner and edge information. Phase congruency is a dimensionless quantity and provides information that is invariant to image contrast. The minimum and maximum moments provide feature information in their own right. If the maximum moment of phase congruency at a point is large then that point should be marked as an edge. If the minimum moment of phase congruency is also large then that point should also be marked as a `corner'. The hypothesis being that a large minimum moment of phase congruency indicates there is significant phase congruency in more than one orientation, making it a corner.

Rather than assume a feature is a point of maximal intensity gradient, the Local Energy Model postulates that features are perceived at points in an image where the Fourier components are maximally in phase The measure of phase congruency :

$$PC1(x) = \frac{|E(x)|}{\sum_n An(x)} \tag{15}$$

Under this definition phase congruency is the ratio of $|E(x)|$ to the overall path length taken by the local Fourier components in reaching the end point. The complex vectors would be aligned when all the fourier components are in phase and the resulting ratio of $\frac{|E(x)|}{\sum_n An(x)}$ would be 1. When noise compensation is also considered, the new measure is given by:

$$PC(x)=\frac{\sum_n W(x)\lfloor An(x)\Delta\Phi(x) - t\rfloor}{\sum_n An(x) + \varepsilon} \tag{16}$$

$$\Delta\Phi(x)=\cos(\varphi_n(x) - \bar{\varphi}(x)) - |\sin(\varphi_n(x) - \bar{\varphi}(x))| \tag{17}$$

The term W(x) is a factor that weights for frequency spread (congruency over many frequencies is more significant than congruency over a few frequencies). A small constant, ε is incorporated to avoid division by zero [9]. After the edge significance is calculated by the phase congruency model, points along the extracted edges are utilized to quantify the similarity of the reference and sensed image by calculating the modified Hausdorff distance between these two point sets (i.e., CPA and CPB). The original Hausdorff distance quantifies the point sets' resemblance by measuring the distance of the point in CPA that is farthest from any nearest point in CPB. Smaller distance is always preferred because the two data sets will be close enough.; whereas with only one extra outlier, a large Hausdorff distance exaggerates the mismatch. The sum of the distances as the measurement of resemblance and transform the sum by Gaussian function will reduce the influence of outlier[10]. This measurement is defined as SI.

$$SI_{A,B}= \sum_{cpA\in CPA} h\left(\min_{cpB\in CPB} \|cpA - cpB\|\right) \tag{18}$$

where

$$h(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}. \tag{19}$$

3.2 Mutual information: Mutual information is the amount by which the uncertainty about B decreases when A is given: the amount of information A contains about B. Because A and B can be interchanged, I(A,B) is also the amount of information B contains about A. Registration is assumed to correspond to maximizing mutual information [7]. The images have to be aligned in such a manner that the amount of information they contain about each other is maximal:

$$M\,I(A,B) = H(A) + H(B) - H(A,B). \tag{20}$$

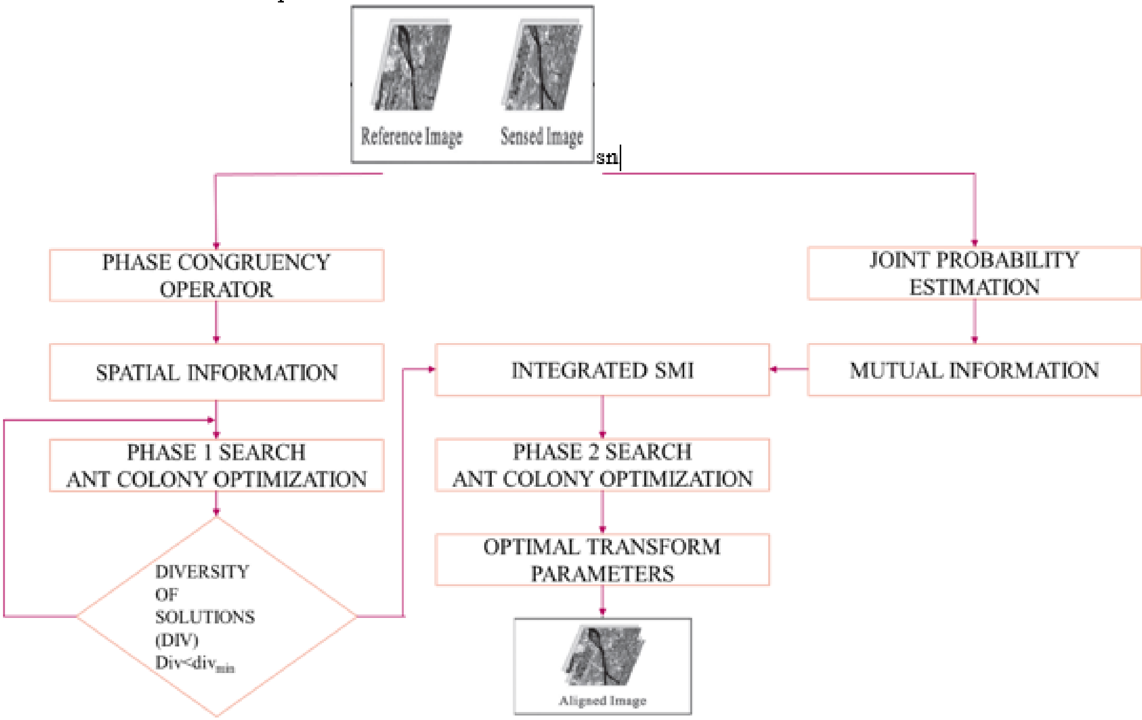

Fig 2: Integrated SMI method

normalized measure of mutual information which is less sensitive to changes in overlap:

$$NMI(A,B) = (H(A) + H(B))/(H(A,B)) . \qquad (23)$$

Maximum value of MI indicates that the two images are geometrically aligned [11-13].

3.3 ACOR Meta-Heuristic: The major algorithmic components of ACOR are 1) solution construction, 2) pheromone update, and 3) daemon action. The first two components are used to search for a solution based on meta-heuristic. The third component is used to determine the iterative stopping condition. Here an n dimensional optimal solution $s*\in X$ is generated from the search space $X \subseteq Rn$, with constraints Ω, in order to maximize an objective function $f : X \rightarrow R$. In this case of image registration, X is the transformation parameter (rotation, horizontal, and vertical displacement) and f is the similarity metric, integrated SMI; $s*$ represents the optimal transformation that maximizes SMI, containing n parameters (n = 3 in the experiment). When the iteration is stopped the best solution is returned. Meanwhile, the termination conditions such as number of iterations, improvement of the objective function, or difference between the best and worst solutions, will be examined. In this case, when the desired condition, iterations tmax, is met, the optimization process will terminate [14].

IV. EXPERIMENTAL RESULTS

The above methods are applied to the registration of remote-sensing images derived from Landsat TM, SPOT, and SAR. The methods generally outperforms other normal registration methods. While considering Integrated SIFT & MI, at first the SIFT approach equipped with a reliable outlier removal procedure can guarantee the preregistration results close to the solution. Second, the MI is more accurate and the modified Marquardt–Levenberg search strategy combines the efficiency of the Newton method with the robustness of the gradient method.Regarding computational efficiency, for SIFT-based matching, the computational cost is relative to the number of detected key points. For example, the number of key points detected from the one image pair is much larger than that of those from another image pair, and hence, the preregistration process for the first image pair requires much higher computational time. For the MI-based methods, the computational cost is proportional to the number of MI evaluations.

The experimental results of Integrated SMI metric indicate that this registration approach can achieve sub-pixel accuracy without predefining the parameter range with a relative satisfactory speed.The method will substantially reduce human supervision of selecting ground CPs and greatly improve its robustness in multisensor image registration.

V. CONCLUSION

Integration of area based and feature based methods area new system for performing efficient and robust registration for remotely sensed images. This paper presents the recent innovative trends in the area of automatic image registration. On the contrary the above methods still has some operational limitations. The registration of multi view images with the difference in the terrain elevation and acquisition angle, the affine transformation model applied in this work is not suitable. Other more appropriate transformation models such as thin-plate spline can substitute the affine model in the proposed coarse-to-fine scheme to handle the effects introduced by the acquisition angle and terrain elevation differences.

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