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Advanced Approach for Image Decomposition and Registration of Large Images

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ABSTRACT: In this paper, matching of planetary images are considered. When dealing with planetary images of the same area acquired at different times, it is straightforward that due to natural processes such as dust deposition or geological phenomena, the images may not be perfectly co-aligned. In such applications, it is desirable to have a sub-image ranking according to the matching quality that was achieved. Feature based method establish a correspondence between a number of especially distinct points in images. When implementing coupled decomposition with the feature based matching technique, the problem of fast and accurate extraction of points that corresponds to the same location from a pair of large sized images can be addressed. The coupled image decomposition technique imposes spatial constraints on matching process without employing sub-sampled versions of reference and target images. Here a detailed study of the performance of coupled decomposition technique with the Scale Invariant Feature Transform (SIFT) descriptor and the simulation results are presented.

KEYWORDS: Image matching, Planetary Image, Sub-image ranking, SIFT, Coupled Decomposition.

I. INTRODUCTION

From the invention of smart-phones and digital cameras, tens of megapixel images are generated for the availability of the public. The planetary mapping are high resolution images with several megapixels. Image pairing is a technique that is used mainly for the matching process of large images with different resolution and parameters. When dealing with large images feature based matching techniques were used.

Image matching mainly focus on the tie-point matching or the characteristic image curves. Image matching is done using characteristics of these features and this helps in limiting the cost of computation. Image registration is the process of transforming different sets of data into one coordinate system. Data may be multiple photographs, data from different sensors, times, depths, or viewpoints. It is used in computer vision, medical imaging, biological imaging and brain mapping, military automatic target recognition, and compiling and analyzing images and data from satellites. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements.

When dealing with large images, the tie-point increases with the size of the images. The feature based matching of the image become complex only when the number of feature points increases. The state-of-the art techniques were used in matching for increasing the computation speed of the process of the normal sized images. In the full image matching process, the tie-point extracted actual areas are ignored and this will result in the reduction of computational time required for the matching of large images. The pyramidal schemes are used to reduce the computational cost. In this scheme, a number of sub-sampled versions of reference and target images are used. This scheme is fully dependent on the successful matching of intermediate resolution version.

In coupled decomposition technique, the image matching is performed at the sub-image level. The algorithm performs the matching of two images by considering the neighborhood features, i.e., the output defines image neighborhood for the features in one image and restricts matching into the corresponding neighborhood in the other image.

The full-image matching of large images is associated with degraded accuracy, which cannot be improved through parameter tuning is showed. This analysis derives from the fact that matches are typically identified through the nearest neighbor distance ratio (NNDR), i.e. the ratio of the distance to the nearest neighbor over the distance to the

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second nearest neighbor. Image registration or image alignment algorithms can be classified into intensity-based and feature-based. One of the images is referred to as the reference or source and the others are respectively referred to as the target, sensed or subject images.

Image registration involves spatially registering the target image to align with the reference image. Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features such as points, lines, and contours. Intensity-based methods register entire images or sub-images.

Image registration algorithms can also be classified according to the transformation models they use to relate the target image space to the reference image space. The first broad category of transformation models includes linear transformations, which include rotation, scaling, translation, and other affine transforms. Linear transformations are global in nature, thus, they cannot model local geometric differences between images. The second category of transformations allow 'elastic' or 'nonrigid' transformations. These transformations are capable of locally warping the target image to align with the reference image.

In this paper, the coupled decomposition technique is implemented on the mars planetary by using the Nearest Neighbor Distance Ratio and the Scale Invariant Feature Transform(SIFT).Coupled decomposition is a two step iterative process, at each iteration, before image decomposition, the sub-images will be coupled. The image matching will be performed from the base level to the finest level. While matching full images at the low resolution, the results will be updated at the finest resolution. The coupled decomposition implemented before uses the interest point detector and the local descriptor

The rest of the paper deals with the related works that has been implemented before and the next section deals with the implementation of the coupled decomposition on the planetary images. On the final section, the result of the implementation is explained.

II. RELATED WORKS

A. Tie-point matching

The standard tie-point matching process makes use of two image pairs, say, X and Y which consist of two independent descriptive points. Different tie-point extraction techniques, such as SURF, GLOH, SIFT and DAISY are widely used. among these descriptors, DAISY descriptor has more advantage than the other techniques.

DAISY is the local descriptor, which is very efficient for dense computation. An EM-based algorithm to compute dense depth and occlusion maps from wide-baseline image pairs using this descriptor was used. This yields much better results in wide-baseline situations than the pixel and correlation-based algorithms that are commonly used in narrow baseline stereo. Also, using a descriptor makes the algorithm robust against many photometric and geometric transformations. Unlike SURF, which can also be computed efficiently at every pixel, it does not introduce artifacts that degrade the matching performance when used densely. No matter which descriptor is employed, when dealing with either large datasets of small images or very large images, the most time-consuming stage of the pipeline is point matching.

Optimal Linear Projection is a method to transform an image descriptor so that nearest neighbor (NN) search for correspondences becomes the optimal matching strategy under the assumption that inter-image deviations of corresponding descriptors have Gaussian distribution. The Euclidean NN in the transformed domain corresponds to the NN according to a truncated Mahalanobis metric in the original descriptor space. Distinctive image features from scale-invariant key-points, describes an approach for using the features for object recognition. The recognition proceeds by matching individual features to a database of features from known objects using a fast nearest-Neighbor Algorithm followed by a Hough transform to idnetify clusters belonging to a single object, and finallay performing verification through Least- Squares solution for consistent pose parameters. This approach to recognition can robustly identify objects among clutter and occlusion while achieving near real time performance.

SURF (Speeded Up Robust Features) is a novel scale- and rotation-invariant interest point detector and descriptor which approximates or even outperforms previously proposed schemes with respect to repeatability, distinctiveness, and robustness, yet can be computed and compared much faster. This is achieved by relying on integral images for image convolutions; by building on the strengths of the leading existing detectors and descriptors and by simplifying these methods to the essential. This leads to a combination of novel detection, description, and matching steps.

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Advances in image acquisition system had made it possible to capture high resolution images of a scene, recording considerable scene details. With increased resolution comes increased image size and geometric difference between multi-view images, complicating image registration.Through Voronoi subdivision, it is possible to subdivide large images into small corresponding regions, and by registering small regions, register the images in a piecewise manner. Image subdivision reduces the geometric difference between regions that are registered and simplifies the correspondence process.The hierarchical Voronoi system is a hierarchical one. While previous methods use the same block size and shape at a hierarchy, this method adapts the block size and shape to the local image details and geometric difference between the images. This adaptation makes it possible to keep geometric difference between corresponding regions small and simplifies the correspondence process.This method proposed can withstand considerable outliers and local geometric differences between images. It also remains efficient when the point sets to be matched are very large.

Image registration by super curves is the 2-D affine image registration problem by curve matching and alignment is solved. This approach starts with a super-curve, which is formed by superimposing two affine related curves in one coordinate system. This method uses B-spline fusion technique to find a single B-spline approximation of the super-curve and a registration between the two curves simultaneously.

Consistency of image edge filtering is of prime importance for 3D interpretation of image sequences using feature tracking algorithms. To cater for image regions containing texture and isolated features, a combined corner and edge detector based on the local auto-correlation function is utilized, and it is shown to perform with good consistency on natural imagery.

Matching between edge images on a pixel-by-pixel basis works for stereo, because of the known epi-polar camera geometry. However for the motion problem, where the camera motion is unknown, the aperture problem prevents us from undertaking explicit edgel matching. This could be overcome by solving for the motion beforehand, but we are still faced with the task of tracking each individual edge pixel. Tracked edge connectivity, supplemented by 3D locations of corners and junctions, can provide both a wire-frame structural representation and delimited image regions which can act as putative 3D surfaces.

A novel fast SIFT (Scale Invariant Feature Transform) feature matching algorithm for image registration is used for the extraction and matching of large images. For fast SIFT feature matching, the proper number of leaf nodes are chosen to optimize the priority k-d tree search algorithm in a single k-d tree.In order to get the relationships among the number of SIFT features and the precisions achieved by the priority k-d tree search algorithm in a single k-d tree, the properties of a single k-d tree and that of the priority k-d tree search algorithm are combined.Referring to these relationships, a proper valuecan be selected to achieve an approximate precision in fast time. In order to improve matching precision, the bi-directional priority k-d tree search algorithm is described, i.e., the priority k-d tree search algorithm is used twice.

B. Intensity-Based Vs Feature-Based

Image registration or image alignment algorithms can be classified into intensity-based and feature-based. One of the images is referred to as the reference or source and the others are respectively referred to as the target, sensed or subject images. Image registration involves spatially registering the target image to align with the reference image. Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods find correspondence between image features such as points, lines, and contours. Intensity-based methods register entire images or sub-images.

If sub-images are registered, centers of corresponding sub images are treated as corresponding feature points. Feature-based methods establish a correspondence between a number of especially distinct points in images. Knowing the correspondence between a number of points in images, a geometrical transformation is then determined to map the target image to the reference images, thereby establishing point-by-point correspondence between the reference and target images.

Image registration algorithms can also be classified according to the transformation models they use to relate the target image space to the reference image space. The first broad category of transformation models includes linear transformations, which include rotation, scaling, translation, and other affine transforms. Linear transformations are global in nature, thus, they cannot model local geometric differences between images. The second category of transformations allow 'elastic' or 'nonrigid' transformations. These transformations are capable of locally warping the target image to align with the reference image. Non-rigid transformations include radial basis functions, physical continuum models, and large deformation models.

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Registration methods may be classified based on the level of automation they provide. Manual, interactive, semi-automatic, and automatic methods have been developed. Manual methods provide tools to align the images manually. Interactive methods reduce user bias by performing certain key operations automatically while still relying on the user to guide the registration. Semi-automatic methods perform more of the registration steps automatically but depend on the user to verify the correctness of a registration. Automatic methods do not allow any user interaction and perform all registration steps automatically.

C. Planetary Image Matching

The planetary image matching is an important in the field of space monitoring. The matching of planetary images mainly concentrates on the accuracy of matching. Any matching error is likely to result in distortions being re-projected in geo-coded images and/or maps, which are going to be used in tasks that require high accuracy. a typical remote sensing image is on the order of tens-to-hundreds of megapixels, and can reach up to 10 giga-pixels. Brute-forcetie-point matching are very likely to result in a prohibitivecomputational cost. The combined requirements for highaccuracy and reliability with a realistic computational timeleads to the manual decomposition of the input images intocorresponding, non-overlapping sub-images.

The figure1 shows the example of a planetary image from Martian imagery.

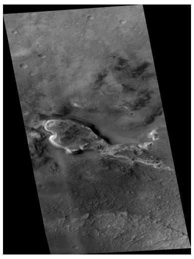

Fig.1. An example of a planetary image

III. SYSTEM OVERVIEW

When dealing with planetary images of the same area acquired at different times, it is straightforward that due to natural processes such as dust deposition or geological phenomena, the images may not be perfectly co-aligned. In such applications, it is desirable to have a sub-image ranking according to the matching quality that was achieved. In this way, a measure is attained that enables a discrimination between un-changed and potentially-changed areas. A novel adaptive image manipulation technique, which is name coupled image decomposition is proposed. This is a two-step, iterative, global-to-local algorithm. At each iteration, the corresponding images (or sub-images) are initially coupled, before a concurrent image decomposition process generates multiple corresponding sub-images. The coupled decomposition algorithm output defines an image neighborhood for each feature in the first image and restricts matching into the corresponding neighborhood in the other image. Figure 2 shows the block diagram of the matching of large planetary images using coupled decomposition with Scale Invariant Feature Transform and nearest neighbor distance ratio.

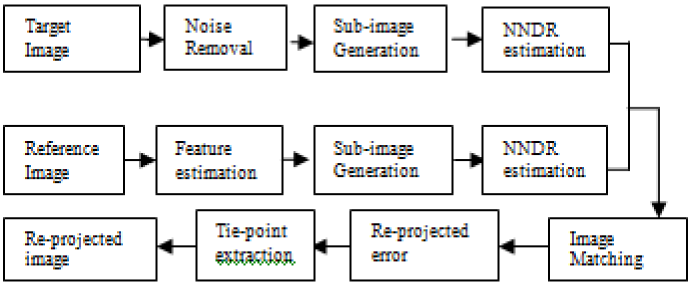

Fig.2.Block diagram of coupled decomposition

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Full-image matching of large images is associated with an increased computational cost, since image matching by default has quadratic computational complexity. Here the full-image matching of large images is also associated with degraded accuracy, which cannot be improved through parameter tuning is showed. This analysis derives from the fact that matches are typically identified through the nearest neighbor distance ratio (NNDR), i.e. the ratio of the distance to the nearest neighbor over the distance to the second nearest neighbor. For example, in the original SIFT publication a point in the reference image was declared matched if NNDR was less than a threshold H = 0.8, while it was further claimed that the exact threshold value is not critical on the matching performance.

When matching two sets of feature points coming respectively from the reference and the target image, it is fair to assume that the distances between a feature point in the reference image that does not have any match in the target image and all *NW* feature points in the target image are random, i.e. coming from a distribution *fD(d)*(the corresponding cdf is $F_D(d)$).

Then the joint distribution of the distance to the nearest neighbor d_1 and the second nearest neighbor d_2 is given by,

$$f_{D_1,D_2}(d_1, d_2) = N_W(N_W-1)F_{D_1}^{Nw-1}(d_1)f_{D_1}(d_1)f_{D_2}(d_2) \quad (1)$$

where $d_1 \leq d_2$. The probability P of correct rejection is the probability of $d_1 \leq Hd_2$, which is given by,

$$P = N_W(N_W-1)\int_{-\infty}^{\infty} F_{D_1}^{Nw-2}(d_1)\, f_{D_1}(d_1)\left(\int_{d_1}^{Hd_1} f_{D_2}(d_2)dd_2\right)dd_1$$

$$= \int_{-\infty}^{\infty} F_{D_1}^{Nw-2}(d_1)\left(F_{D_1}(Hd_1) - F_{D_1}(d_1)\right) f_{D_1}(d_1)dd_1 \quad (2)$$

On expanding the above equation the probability P becomes,

$$P = N_W(N_W-1)[\int_{-\infty}^{\infty} F_{D_1}(Hd_1)F_{D_1}^{Nw-2}(d_1)f_{D_1}(d_1)dd_1$$

$$-\int_{-\infty}^{\infty} F_{D_1}^{Nw-1}(d_1)\, f_{D_1}(d_1)dd_1 \quad (3)$$

Since $\int_{-\infty}^{\infty} N_W F_{D_1}^{Nw-1}(d_1)f_{D_1}(d_1)dd_1$ =1 this equation becomes,

$$P = 1 - N_W H\int_{-\infty}^{\infty} f_{D_1}(d_1)F_{D_1}^{Nw-1}(d_1)dd_1 \quad (4)$$

The mis-detection ratio E_{md} is given by,

$$E_{md} = N_W H\int_{-\infty}^{\infty} f_{D_1}(d_1)F_{D_1}^{Nw-1}(d_1)dd_1 \quad (5)$$

Equation (5) implies that the mis-detection ratio is determined by the distribution $f_D(d)$, the threshold H and the number of tie-points in the target image N_W. Following a similar rational can conclude that the false rejection ratio and the mis-classification ratio is also determined by the above parameters, along with the distribution of the matching feature point distances $g_D(d)$.Consequently, this parameterization can be employed to examine matching performance dependence from the number of points $N_W$and the NNDR threshold H. In this implementation, it is assumed that correct matches show consistently low distance values, thus $g_D(d)$ was selected as a uniform distribution with minimum value 0.01 and maximum value 0.1. On the other hand, $f_D(d)$ was supposed to be a normal distribution, with mean value 0.5 and variable standard deviation σ. The above selections reduce the number of degrees of freedom to 3: the standard deviation σ, the threshold H and the number of tie-points in the target image N_W.

In the state-of-the-art approach, initially interest point detection is conducted on the reference and the target image, before processing the extracted informative image points to generate local descriptors. Thus, a point is projected from image space to descriptor space. During matching, each target image descriptor is matched with a reference image descriptor or discarded if no match is found, and the matches are re-projected from the descriptor space to the image space. This approach does not impose any spatial constraints on the matching process, which is fully conducted in the descriptor space, while pyramidal schemes impose spatial constraints based on sub-sampled versions of the images, a strategy that is problematic when dealing with large images. In this section we introduce a novel technique, named coupled decomposition, imposing spatial constraints on pairs of images using only the full resolution images, which subsequently are matched.

The set of corresponding sub-images, which is the output of coupled decomposition, can be used to develop several image matching solutions that focus either on the decrease of the computational complexity required for image

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matching or on exploiting the information redundancy associated with the fact that all sub-images belong to the same image.

The coupled decomposition outcome is used to impose spatial constraints on the tie-points of the target image that can be matched to the tie-points of the reference image. When no overlap is used this is equivalent to decomposing both reference and target images in corresponding sub-images and performing tie-point extraction independently on each pair of sub-images, before aggregating the identified tie-points. A non-zero overlap rate *a* can be used to determine the tradeoff between computational complexity and the number of identified tie-points.

Supposing that in the reference image (the target image) the total number of extracted interest points are $C_Z(C_W)$, the candidate matches that need to be checked are reduced from $C_Z\ C_W$to $\sum C_{Z_i} C_{W_i}$, where *i* is the sub-image index. In large images, in which $C_Z$and C_W may be on the order of millions, this constitutes a substantial computational gain. In this section, we demonstrate that the computational gain increases with K and decreases with overlap rate *a*.

In order to establish this property for mean-based coupled decomposition, it is initially assumed that $a = 0$, M is the number of radial sections per iteration, K the total number of iterations, and $C_Z$and $C_W$the total number of tie-points in Z and W, respectively. Then the average number of tie-points in each sub-image would be $C_Z\ /M^K$and C_W/M^K. Moreover, the fact that the image centroid usually lies near the image center implies that, generally speaking, $C_{Zi}$and C_{Wi} are more probable to take values near their average than take extremely low or high values, i.e. that the probability density function maximum and the average value coincide. $C_{Zi}$and $C_{Wi}$are not expected to be mutually independent, since coupled decomposition generates pairs of matching sub-images.

IV. EXPERIMENTAL RESULTS

A. Input images

The performance of the coupled decomposition system is analysed by simulating the target and reference images using the MATLAB software. The inputs provided to this system are target image and reference image.

Figure.3(a).shows the input target image provided to test the performance of the proposed technique.The target image can beof any resolution and can be of any color space. The image should be in the JPEG format.

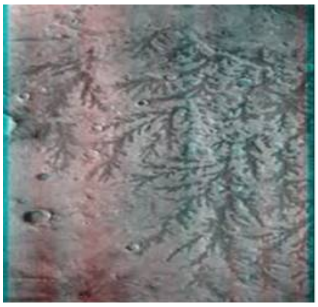

Fig.3(a)

Fig.3(b)

Fig.3.Input target and reference planetary images

Figure 3(b) shows the reference image that is used as an another input to test the performance of the proposed technique. The reference image will always be more clear and accurate image. The resolution of the reference image will be more than that of the target image. The reference image can be of any color space and the image will be in the JPEG compression standard.

Figure4(a) and figure(b) shows the grayscale converted target image and reference images. The grayscale conversion is done to perform the noise removal accurately. The noise removal can be applied only on the grayscale image.

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Fig.4(a)

Fig.4(b)

Fig.4. Grey-scale images of target and reference images

Figure5(a) and figure5(b) show the tie points extracted target image and reference. The tiepoint extraction is done by using the SIFT detector. The coupled decomposition outcome is used to impose spatial constraints on the tie-points of the target image that can be matched to the tie-points of the reference image.

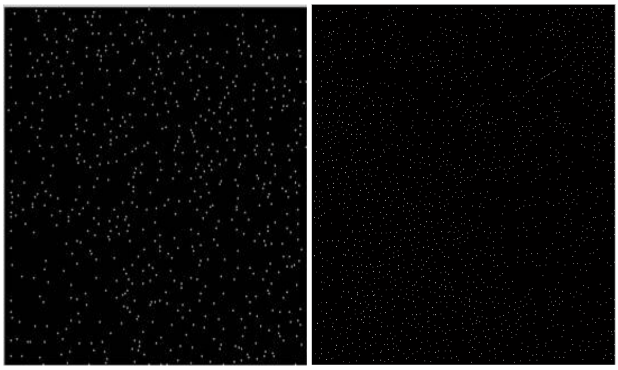

fig.5(a)

Fig.5. Tie-point extracted target and reference images

Figure.6.shows the matched image of the target and reference image. The comparison of the parameters in the both images results the matched image. Whenmatching two sets of feature points coming respectively from the reference and the target image, it is assumed that the distances between a feature point in the reference image that does not have any match in the target image and all feature points in the target image are random.

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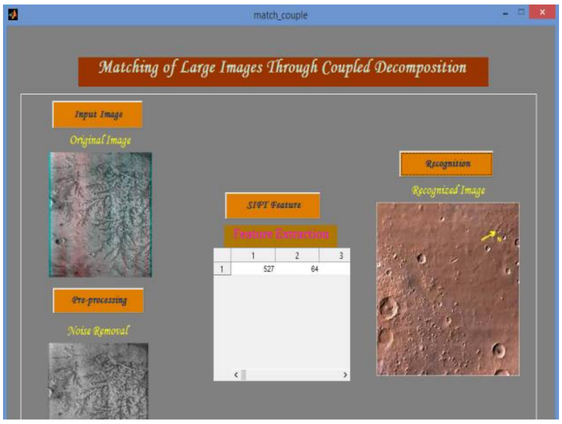

Fig.6. Matched image through coupled decomposition

V. CONCLUSION

A novel technique called coupled image decomposition is implemented and this technique has demonstrated that it can be used to circumvent the computational cost boost that is usually associated with the matching of massively sized images, whilst generating information that may both enhance the achieved accuracy and estimate local regions that cannot be successfully matched. The problem of fast and accurate extraction of points that correspond to the same location (named tie-points) from pairs of large-sized images is addressed A theoretical analysis of the performance of the full-image matching approach, demonstrating its limitations when applied to large images.Subsequently, introduce the coupled decomposition technique to impose spatial constraints on the matching process without employing sub sampled versions of the reference and the target image,. This technique splits images into corresponding subimages through a process that is theoretically invariant to geometric transformations, additive noise, and global radiometric differences, as well as being robust to local changes. coupled image decomposition can be used both for image registration and for automatic estimation of epipolar geometry. Finally, coupled image decomposition is tested on a data set consisting of several planetary images of different size, varying from less than one megapixel to several hundreds of megapixel.

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