**Advanced selective key point detection techniques**

**Original Article**

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**Abstract**

SAR imaging needs precise registration process to get recompensation or setoff between two or more images for a certain area. Generally, operational goal of registration process is a geometrical transformation for the input leading to geometrically agreement for input images. Coregistration step can be used in a lot of fields as change detection, mosaicking, super-resolution images creation, … etc. Registration process can be classified into two main classes: Classical or Automatic methods. For the classical approach, the anchor points are picked out manually and then the transformation modeling is performed, that leads to more time consuming and low output accuracy. Automatic detection of these anchor points aims to recover the functionality of non-automated processes. Registration process should recover many problems such as illumination changes, variations of intensity, Different sensors, noise, … etc. Its applications are mainly dependent on errors, such as multi temporal, multi view, or multi modal, occurred during capturing process. Feature detection, as a step of image registration process, obtains a group of anchors, that are stable and informativeness, or patches under varying conditions. Also, it is critical for the detector to have robustness against viewpoint changes, brightness changes, and other deformations. Detailed discussion and investigation are paid, in this manuscript, for the common corner detectors helping to be familiar with the various applied techniques for feature detection. Our goal is to examine a combination hypothesis of these methods into an advanced selective one.

**Keywords:**
Corner detector, feature, Harris reflector, image registration, key point.

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I. INTRODUCTION

Detection process of features is very important to represent the image[1-9]. There are two main approaches for automatic registration. Firstly, Area Based Matching methods (ABM), may be called as coarse co-registration, is pixel-to-pixel registration process. It includes methods as Fourier, correlation, mutual information, and optimization. ABM methods emphasize the existence of features rather than their detection, i.e. no features are detected. Secondly, Feature Based Matching methods (FBM) or fine co-registration as may be called, is subpixel-to-subpixel process. Each one of these two approaches have its own advantages and drawbacks[10, 11, 12]. Features may be points (corners, interest), edges, blobs, texture, or color[1-5, 8, 9, 11, 12]. In general, there are two types of features that can be detected, global and local features. Generally, the content of image is depicted totally using global features, whereas the process of image keypoints detection requires the local one’s usages, their representation is as shown in figure 1[11, 12, 13, 14, 15].

Global features have the drawback of image clutter and occlusions which limit the usefulness of the description. To handle the limitations of global features, its desired to do one of the following: 1) image segmentation[16, 17] only for a few regions or 2) image sampling[18, 19] for different image subparts and this bordered the extent of potential applications[11, 13]. The expectation of local features being more useful than global ones is based on their specifications which are mainly dependent on ascendant performance, structure stability, and informativeness property[8, 9, 20, 21]. To get correspondences among images, it is required to distinguish a set of noteworthy points in each one[22]. Various techniques of feature detection have been proposed and were planned to adequate a certain
purpose as staff matching\cite{1, 2,11}. The best execution is mainly dependent on the parameters of the detector\cite{11-14, 23}. The detectors must have specific characteristics depending on the application as robustness, repeatability, accuracy, generality, efficiency, and quantity. Good feature should be repeatable, informativeness, localized\cite{2, 11-16}. It must be noticed that not all the properties or characteristics of the detector can be fulfilled simultaneously for example properties of distinctiveness and locality\cite{14, 15, 24}.

(a) Global features 
(b) Local features

\textbf{Fig. 1:} Representation of image features

Corner can be illustrated as the intersection point of two or more different directions of rims\cite{11, 13, 24}. Accuracy of features detection, specially corners, is difficult under imperfections of data such as radiometric (illumination changes and/or different sensor characteristics) and geometric (scaling, translation, rotation, affine, projective, or nonlinear differences) differences. So, it is desired to detect the same features in the images in spite of these imperfections. Scaling, translation, and rotation problems can be easily recovered since there is no change in the shape of information. But; with respect to affine, projective, and nonlinear problems, the process is more difficult to be handled since the shape of information changed\cite{12, 13}. Therefore, features detection methodology should be insensitive to common geometric and radiometric changes\cite{1, 2, 4, 10-16, 24}.

Commonly used techniques to acquire corners are contour curvature-based methods, intensities based on derivatives methods, exploitation of color information, human visual system, model-based methods, segmentation-based methods, and machine learning techniques\cite{1, 2, 4, 11, 14-16}. Examination of the performance of a corner detector, basically; started with artificially created images with various types of junctions associated with different lengths, contrasts, angles etc. This approach can make simplification for the evaluation process but cannot model all imperfections which affect the performance of a detector in a real case, so; the results of performance are often over-optimistic\cite{1, 14, 15}. Evaluations of both performance and quality of different key point detection methods were discussed\cite{25-26}. Finally; Merging several key point detection techniques is useful if it is handled well\cite{24, 27}.

**II. COMMON CORNER DETECTORS**

Detection operation of feature can be classified into three classes of corner detection template, contour, and direct detection\cite{24, 28, 29}. Also, it can be categorized according to the operating scale into single scale, multi-scale, and affine invariant\cite{1, 11, 12, 24}. As mentioned before, the aim of this paper is helping readers who is looking forward to be familiar with the different applied techniques used for feature detection.

**II.1. Moravec Corner Detection**

Moravec’s detector\cite{30} is a single-scale Detector. It is one of the earliest approaches that specifies a key point to be that of low essence similarity. Each image’s pixel is investigated by achievement of correlation among overlapping patches such that, the omni-directional correlation’s strength disclosures data about this pixel\cite{11-14, 24}. Strength of corner is acquainted, as the smallest sum of squared differences (SSD), between the patch and its neighbors for main directions (horizontal, vertical, and diagonals), where the moment at which SSD reaches a local maximum; a corner (interest point) is detected\cite{31}. Figure 2 depicts how to achieve the non-maximum suppression operation\cite{11}.
Both existence of noise, can be recovered by smoothing, and increasing the size of window reduce the number of detected feature points and subsequently number of symmetric points. When calculating differences in eight directions, the output befits invariant to rotations that are a multiple of 45 degree[13].

Advantages of Moravec’s detector are as following: a) detecting the lump of the corners, and b) requires less computation than finding the central moment at a window of the same size. While, the disadvantages of Moravec’s detector are: a) it is not isotropic, and b) its computing is shrill[11-14].

II.2. Harris Corner Detector

Harris corner detector[12] is a single scale derivatives-based detector that had been advanced to handle the of Moravec’s constraints by getting the correlation changes for different orientations. It can be considered as a combination of both edge and corner detectors, mainly for gray scale images[11-14, 23, 36, 37]. The gist idea is calculation of the eigenvalues for a slight patch. Then, using the two highest eigenvalues to estimate a specific function which is used together with a threshold to detect the corners which have an ill-defined gradient as shown in figure 3[13]. Its main target, for feature orientation, is to obtain the fastest and slowest change directions by using local directional derivatives covariance matrix[23, 33]. Also, improvements over the Moravec method based on Harris were done by Schmid[14] and B. Sirisha[33] developed a detector to be utilized for the color information[11, 33].

Harris corner detector has many advantages as following: 1) it has robustness against variations of rotation, translation and illumination ; 2) it is high discriminative, localized, and repetitive ; 3) it is the most stable one in many independent evaluations ; 4) it provides high rotational invariance repeatability[11-14, 23, 24, 36, 37]. The Disadvantages of Harris corner detectors are: 1) it may be sensitive to noise ; 2) it has more expensive computations requirements ; 3) it is sensitive to high scale changes[11, 14, 23].

Shi, Tomasi[38] was developed as an optimization based on Harris method. Shi, Tomasi allow the usage of the minimum eigenvalues for differentiation and considerably thus regulates and facilitates the computation of Harris[11, 23].

Since developing the robustness of the detector to different types of transformations requires being invariant to affine transformations, so; Harris Laplace / Harris Aline[39, 40] were developed, based on Harris method, to act as a multi-scale affine invariant corner detector. The main idea based on a blend of Harris method and a gaussian scale space representation allowing detection of features over a range of scales[11-14, 23].

Their advantages are: 1) it provides a high informative group of anchors in the scale dimension ; 2) it has a robustness against changes of scale ; 3) Also, it has a robustness against noise, illumination ; 4) it has high repeatability rate. Their disadvantages are: 1) reduction the excessive number of anchor points comparing to other multi-scale techniques as Laplacian of Gaussian (LoG) or Difference of Gaussian (DoG), and 2) it has bad performance with respect to affine transformations[11, 12, 23].

Tuytelaars and Van Gool[41, 42] developed, based on Harris method, a different approach depending on local invariants which distinguish neighborhoods of interest points. The cause backwards this tendency is that rings are counted as settled features that can be distinguished over multiple changes as illumination, viewpoints, scaling. Further, by utilizing the geometry of the edge, the dimensionality of the issue can be safely diminutive[11-14, 23].

II.3. SUSAN Corner Detectors

Susan corner detector[43] is a single scale detector which does not smooth the image or use locative derivatives. It uses a morphological approach as an unlike way rather than estimating gradients of local which may be sensitive to noise and more cost computations. Smallest Univalue Segment Assimilating Nucleus (SUSAN) has been used as a corner detection and edge detection besides noise suppression where an annular disguise is utilized concerning each pixel, and checking the gray accounts concerning all pixels inside the disguise then comparing with that of central one[11-14, 23]. Corners can be distinguished as the locations where the number of same intensity records in a regional vicinity catches a local floor and beneath a specified onset as shown in figure 4 where A is an edge, B is a corner, and C is neither an edge nor a corner[13, 23]. Increasing
robustness can be achieved using weighting coefficient where Unvalue Segment Assimilating Nucleus (USAN) represents a grouping of the vicinity, having similar value as the central one, together[11-15, 23, 33]. It has a high performance in spite of noise existence since it does not call derivative[23, 44].

II.5. Robust Fuzzy Rule Corner Detector

Corner detection technique for general purpose, with high performance and efficiency, is a challenge. Starting from this point, a few fuzzy methods have particularly discussed this problem[11, 13, 14, 23]. An algorithm has been proposed by Banerjee and Kundu[49] to extract significant corner points in gray level where the cornerness measuring for each candidate is counted by ways of the vague rim strength. Changing threshold value causing various groups of corners (fuzzy) as shown in figure 6. The main advantage of Fuzzy Rule corner detector is that it may be easily used for detecting different types of anchors. Using different types of detectors, at various stages, causes a high load of computations. This can be considered its main drawback[13, 14, 25].
be returned with many responses, 2) it can provide further interest points that result in a densely objects, 3) it has good performance and repeatability. The drawbacks of hessian detector are: 1) it is sensible to changes of scale, 2) it is sensitive to noise leading to low localization accuracy causing the local maxima to be less stable\cite{11, 13, 14, 23, 40}.

Hessian-Laplace detector\cite{40, 53} was developed to act as a changeless scale blob detector which is a blend of hessian detector and a gaussian scale space illustration. The core is that it operates on local extrema at various scales using DoH for spatially localized, and the Laplacian for localization of the scale. Mikolajczyk, K.\cite{54} is designed to be insensitive to affine, it utilizes Harris based detector, integrating key points from different scales in a pyramid with some reiterated election gauge, and matrix of numbers 1, 5, 9 and 13. If three of these four test pixels are luminous or darker than the intensity value, then a corner can only exist as a first step. For final result, the remaining pixels are examined. FAST detector is similar to SUSAN, but uses a smaller window size in addition to the fact that only some of pixels are examined instead of all of them. It can be rated as a proportion of the local binary pattern LBP\cite{14, 23}.

Hessian\cite{11, 12, 23}. Mikolajczyk and Schmid\cite{53} concluded that the response of hessian detector exists if significant variations over any two perpendicular ways occurred. Also, for a single image, the repeatability, discernment more reliable regions, of hessian affine approach better than that of Harris affine one. In addition, it complies good to regions which have many corners, for example, buildings scenes\cite{11-15, 23, 24}.

The advantages of hessian affine are 1) it has the ability of extraction large number of features, 2) using spatial and scale localization is more suitable for scale estimation, and 3) It has a high stability compared to the Harris one. Although these advantages, hessian affine has a drawback that its repeatability is low compared to Harris-Laplace\cite{11, 52}.

II.7. FAST Detector

Roššen, E., Drummond\cite{56} proposed Features from Accelerated Segment Test (FAST) detector which is a uni-scale keypoint detection. Interest points are categorized by utilizing a part check to the pixel intensity. This can be achieved by concerning a ring (bresenham circle) consisting of sixteen pixels, as base of computation, around the interest point\cite{11, 14, 23, 24}.

The key point can be detected if its intensity rate (I) is larger or junior than the value of a collection of (n) neighboring pixels in bresenham circle as shown in figure 8, taking into account a predefined threshold\cite{11}.

Roššen, E., Drummond\cite{56} developed a test, whose speed is high, to eliminate a considerable number of points which are not corner by investigating only the pixels

![Fig. 7: Components of both Hessian matrix and determinant](image)

\( I_{xx} \times I_{yy} - I_{xy}^2 = 0 \)
II.8. Laplacian / LoG / DoG Detectors

Laplacian operation, is a manner for computing the extreme average of change (derivative) in a pixel. It is described for a gray-scale image\textsuperscript{[11, 14, 23, 24]}. Laplacian of Gaussian (LoG)\textsuperscript{[57]} is a detector dedicated for various scales which is simply combines Laplacian operation over an area that had been treated utilizing a smoothing Gaussian kernel to converge the rim as shown in figure 9\textsuperscript{[12]}. This means that LoG is a linear series of 2nd derivatives and a blob detector. The operator’s output depends strongly on the link between size of the structures of blob and the size of smoothing Gaussian kernel where the scale is controlled by the Gaussian standard deviation by varying the blurring amount\textsuperscript{[11, 23]}. LoG at a pixel in the image becomes locally maximum or minimum when the pixel represents the center of a dark or bright spot respectively\textsuperscript{[12, 14]}.

Lindeberg\textsuperscript{[48]} developed an automatically method, considered to be a local curvature detection, for capturing blobs of different size where the automatic selection of the scale and a multi-scale method is developed such that both curvature of local surface and the magnitude of the gradient are high. It is important to mention that the local curvature methods, as Rosenfeld and Bretzner\textsuperscript{[58, 59]}, were firstly known to be accurate and reliable for focusing anchor points over the changes of the scale\textsuperscript{[11-14, 23, 24]}. Advantage of LoG are: 1) it is invariant to rotation, 2) it provides somewhat a good rating for other features such as corners, ridges, etc., 3) the detected features can represent extended and splitting structures. Disadvantage of LoG are: 1) its computation is time consuming, 2) less stable, 3) more sensitive to noise\textsuperscript{[11, 12]}.

Difference of Gaussian (DoG)\textsuperscript{[60]} can be considered as a multi-scale detector which is utilized to speed up computation of LoG, i.e. DoG provides a nearest access to LoG as shown in figure 10. This can be accomplished using subtraction of the neighbouring levels of the scale of the Gaussian pyramid breaked up by a certain operator without needing for convolution. The operation of DoG efficiently detects the nonvarying keypoints from scale-space, while it suffers from the same drawbacks of LoG \textsuperscript{[11, 23, 40]}. 

Fig. 8: Illustration of operation of FAST corner detector

Fig. 9: Laplacian of Gaussian (LoG) operation
II.9. Salient Regions (Entropy) Detection

Kadir and Brady[61, 62] developed a novel methodology which is established on thought that key points over a multi-scale should present a local characteristics (entropy) that are unexpected compared to the neighborhood region. The entropy method is mainly based on locally maximizing the information content, therefore, the most distinctiveness points can be identified[11, 12, 24, 23]. The most important note for the entropy method is being a rotationally invariant feature since location of pixel are not used in the calculation, therefore the entropy window will not alternate by rearrangement its pixels with respect to the centered window[62, 24].

II.10. Gabor-Wavelet Detector

Gabor-Wavelet detector[29, 63] can be considered as key point detector operating in multi-scale relying on the basis of Gabor wavelet which is stimulated convolution kernels in the modality of plane waves bounded by a Gaussian envelope function[11, 12, 29, 63]. Gabor-Wavelet has many advantages as: 1) it provides the highest and the best ruling for spatial and space frequency domains, 2) It has the ability for improving features of low level like peaks, ridges, etc., 3) It has the capability of extraction of points from different scales, and 4) Its performance is categorized with precision and modification to multiple geometric transformations[11, 12, 29, 63].

II.11. Morphological Interest Regions

Morphological operations[64-68] can be non-varying with respect to both rotation and scale. The prime usage of mentioned method based on creating an interest region on gray scale, binary, or color images. It is important to notice that the process of preparation both gray scale and color images requires many forms of pre-processing operations[23, 62]. The binary thresholding necessitates a part of work to correctly regulate the arguments for a specific exercise to get the highest performance. Generally, the morphological operations alone are not sufficient[1, 23, 62]. Since Maximally Stable Extremal Regions (MSER)[69], feature descriptor technique, is based on the principle of gathering the groups of pixels at maximum or minimum locations, so the morphological interest regions method is similar to MSER, but it is important to know that MSER does not utilize the morphology operators[23].

III. CONCLUSION

Feature detection, as a step of image registration process, obtains a group of anchors, that are stable and informativeness, or patches under varying conditions. It is critical for the conventional detector to have robustness against viewpoint changes, brightness changes, and other deformations. Already existed FBM algorithms suffers from different limitations or deficiencies in dealing with
certain SAR image sets. Our combined, fully automated, advanced selective feature based key method helps to overcome these limitations and deficiencies. A complete discussion of this selective technique had been addressed.

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