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Corner Detection Methods

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Abstract: Corner detection is an approach used within computer vision systems to extract certain kinds of features and infer the contents o f an I m age. Corner detection is frequently used in motion detection, image registration, video tracking, image mosaicing panorama stitching, 3D modeling and object recognition. Corner detection overlaps with the topic of interest point detection. This survey paper gives a broader look into this topic discussing the different techniques used for corner detection, advantages of using these techniques, disadvantages with the methods and success rates.

Key words: Harris Corner · Sliding Window Method · Steerable Filters

INTRODUCTION

A corner can be defined as the intersection of two edges. A corner can also be defined as a point for which there is two dominant and different edge directions in a local neighborhood of the point. An interest point is a point in an image which has a well-defined position and can be robustly detected. This means that an interest point can be a corner but it can also be, for example, an isolated point of local intensity maximum or minimum, line endings, or a point on a curve where the curvature is locally maximal. Corner is interest points in many applications for extracting information from two images. For example, if two successive frames in a video sequence taken from a moving camera can be related, it is possible to extract information regarding the depth of objects in the environment and the speed of the camera. The brute force method of comparing every pixel in the two images is computationally prohibitive for the majority of applications. Corner points are interesting as they are formed from two or more edges and edges usually define the boundary between two different objects or parts of the same object. Many corner detectors have been developed. The use of interested points (and thus corner detectors) to find corresponding points across multiple images is a key step in many image processing and computer vision applications. Some of the most notable examples are: image registration (of particular importance in medical imaging), stitching of panoramic photographs, motion tracking, object detection/recognition, robot navigation and stereo matching.

Corner Detection Techniques: It is desirable for a corner detector to satisfy a number of criteria: all "true corners" should be detected, no "false corners" should be detected, corner points should be well localized, detector should have a high repeatability rate (good stability), detector should be robust with respect to noise and detector should be computationally efficient. The detection of all true corners with no false corners is application (interpretation) dependent since there is no well-defined definition of a gray scale corner. However, in many images the corners are intuitively clear and such images can be used to evaluate the performance of different corner detectors.

Harris Corner Detector: This operator was developed [2] as a low level processing step to aid researchers trying to build interpretations of a robot's environment based on image sequences. Specifically, Harris and Stephens were interested in using motion analysis techniques to interpret the environment based on images from a single mobile camera. They needed a method to match the corresponding points in consecutive image frames, but were interested in tracking both corners and edges between frames. Harris and Stephens developed this combined corner and edge detector by addressing the limitations of the Moravec operator. The result is a far

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more desirable detector in terms of detection and repeatability rate at the cost of requiring significantly more computation time.

A Combined Corner and Edge Detector: It is one of the most famous corner detector [2] from here only the Harris corner detector came out. Chris Harris and Mike Stephens invented this Moravec's corner detector algorithm. Here, they are considering the local window function in the image and determining the average changes of image intensity that result from shifting the window by a small amount in various directions. The Moravec's corner detector may not tolerate the noise in the image. If there is more noise in the image then it may produce fewer results. The Moravec's operator suffers from a number of problems like, a discrete set of shifts at every 45 degrees is considered so the response is anisotropic, an analytical expansion of small shift can be covered by the shift origin, the window is binary and rectangular. So the response will be noisy and the minimum of edge is taken so that the operator responds readily. The corner measure is reformulated to make use of the direction of the shift. Here, detecting corners in a tree image is difficult because lot of discontinuity will be there in the image. By applying low and high threshold edge, hysteris is carried out and the continuity of the edges is maintained. This results in continuous thin edges that generally terminate in the corner regions. The edge terminators are then linked to the corner pixels residing within the corner regions, to form a connected edge-vertex graph. Still the algorithm needs to be enhanced on the part of junction completion algorithm and adaptive thresholding.

Harris Operator Corner Detection using Sliding Window Method: Harris corner detector [3] is used to extract palmprint in form of corners. Here, with Harris corner detector, hamming distance, a similarity measurement using sliding window method is used to get better results. The goal of using hamming distance method for corner detection is that the non-dependency of the method with the number of corner detected. The autocorrelation function has a distinct peak in the image of the corner. Corner detection has found its application in various computer vision tasks. Here, the corner is based on autocorrelation image intensity values or image gradient values. Hamming distance similarity measurement using sliding window method is a new corner matching technique. Sliding window technique is used to avoid false rejection because of displaced ROI. Suppose, if the ROI is placed in two rows, chances are there for the ROI not getting matched with the same ROI present in the same database. Here, to overcome the displacement problem, sliding window method with reduced ROI by some window size WS is used. To get a region of interest the image is pre-processed. Pre-processing includes image enhancement, image binarization, boundary extraction, cropping of palmprint/ROI. The feature extraction is applied on the palmprint image to get corner of the palmprint image. Hamming distance similarity measurement method is used as a feature matching method. From the threshold array the maximum and minimum array are found. The value of reference threshold is chosen where FAR and FRR values are minimum. The comparison time is non-dependent on the number of corner detectors. Here, the number of corners detected is directly proportional to time taken. The combination of Harris corner operator and hamming distance method makes the real time authentication system fast and accurate with less comparison time value and high recognition rate. The advantage of this method is that the corner information extracted using Harris corner detector is compared with the database using sliding hamming distance similarity measurement method using sliding window method. This result shows that the sliding window method takes less time in matching feature vector. Experimental results clearly show that Harris corner detector methodology has the ability to delete similar palmprints with a good accuracy rate of 97.5%. The high accuracy and less comparison time make this system good.

Multi Scale Harris Corner Detector Based on Differential Morphological Decomposition: A novel method for multi scale corner analysis and detection is presented in [4]. First, Harris-Laplace corner detector is used, which helps us for linear scale-space analysis. Secondly, a non-linear scale-space transform, which is Differential Morphological Decomposition, is briefed. This multi-scale transform and the Harris corner indicator are coordinated to build a new multi-scale corner detector. Both corner detectors are visually assessed on synthetic and satellite images, highlighting the advantages of such a method.

The Harris corner indicator algorithm presented by Harris and Stephens is well known technique for making use of the linear filtering of an image. By using the low pass filtering, a Gaussian function of scale finding a position in the image grid. Then the horizontal and vertical image derivatives at the position of the image grid are obtained with the Gaussian filter of local scale. Then the multiplicative operation is performed pixelwise. Then, they filtered by using Gaussian function. As a drawback, integration scale is critical, the small scale result is missing the corner of large objects, when you choose larger scale that will miss small object corners. The integration scale used for performing corner detection is crucial. To overcome this issue a multi-scale Harris corner detection was proposed in by benefiting a linear scale space decomposition. Here, the Harris corner detector is applied in successive integration scales before characteristic scales of image blobs are selected. The Harris corner detector and the scale normalized Laplacian operator are combined in order to detect the salient positions in the scale space grid. The drawbacks of the Harris–Laplace corner detector are: for each scale the local maxima of the Harris indicator are computed secondly, the spatial locations are analyzed through the Laplacian of Gaussian operator, in order to discard the ones which are not salient in the scale dimension. The differential morphological decomposition algorithm (DMD) which is based on the multiresolution pyramid transforms using the opening and closing by a reconstruction operator, a specific DMD is described. The DMD analyzes the image by reducing or coarsing information at each pyramid level. By calculating the difference between the original image and coursing image which is the differential decomposition.

An Object Recognition and Identification System Using the Harris Corner Detection Method: The Harris corner detector [5] is used for image identification. At first, the image is captured using a webcam using the canny edge detector for detecting and the edges and recognizing the image using the Harris corner detector using this identifying triangular, rectangular and rigid circle can be isolated accurately. Before enhancing the image, it has to be processed for the quality of brightness, contrast, or noise. For doing this the fuzzy image processing (FIP) is used. The processes used are image fuzzification, membership modification and image defuzzification. To adjust the brightness of the image the INT operator is used with the matrix X of A x B which is the array of fuzzy singleton of each member represented by the degree of brightness level. If the values are greater than 0.5 increases the brightness of the pixels, the values less than 0.5 decreases the brightness of the pixels. The canny edge detection method is used with Harris corner method for image identification. The Harris corner detector is used for the object identification and shape recognition. The Harris corner detector function is implemented in a robot arm for separating the objects. There are some errors in the experiment because of the lightening affect and angle of the camera.

Corner Detection Using Curvelet and Harris Algorithm: A new corner detection algorithm using Harris corner detector and curvelet finds rotation and scale invariant features [6]. Here the curvelet is a wavelet transform which is helpful in representing the image at different scales and high degree of directionality and anisotropy. The curvlet, like the wavelet, is a multiscale transform, with frame elements indexed by scale and location parameters. This also has directional parameters. The curvelet pyramid contains elements with a very high degree of directional specificity. The curvelet which is based on certain anistropic scaling principle is quite different for the isotropic scaling of wavelets. The corner detection methods such as kitchen and Rosenfeld, Harris and SUSAN were vulnerable to noise and detect this as corner. Because of the noise, it misses fine features and true corners. From the experiments the curvelet toolbox tells that when the number of orientation is six, it gives better localization and minimum number of false corners detection. The performance is evaluated in terms of number of true, false and missed corners detected algorithms. The detection of corner results summary are shown for rotation 00, 300 and 600. The proposed method is compared with SUSAN and Harris. First, an experiment is conducted to detect corners for orginal "house", "block" and " sample" images. Next, original image is rotated with an angle from +900 to -900. It has been observed that proposed method detected minimum number of false and missed corners and good stability, well localized true corners even after rotation of images. The advantage of the Curvelet transform is that it is a wavelet transform with good time-frequency localization and multi resolution and it is based on multi scale levels and multi direction levels. This algorithm detects stable and localized true corners with minimum number of false and missed corners, even after rotation, scaling and testing number of images.

Invariant Corner Detection Using Steerable Filters and Harris Algorithm: In this paper, they propose a invariant corner detection algorithm which combine steerable filters with Harris corner detector. The steerable filters have better orientation selectivity and multi-orientation image decomposition that provide a useful front-end for image-processing and computer vision applications.

Here the performance of this algorithm is better than SUSAN, Harris corner detectors. Steerable filters [7] are spatial oriented filters that can be expressed using linear combinations of a fixed set of basis filters. If the transformation is a translation, then the filter is said to be shiftable or steerable in position; if the transformation is a rotation, then the filter is said to be steerable in orientation or commonly steerable and the basis filters are normally called steerable basis filters. Given a set of steerable basis filters, they can be applied to an image and since convolution is linear, we can interpolate exactly, from the responses of the basis filters, the output of a filter tuned to any orientation we desire. The basic idea is to generate a rotated filter from a linear combination of a fixed set of basis filters. A general architecture for steerable filters, which consists of a bank of permanent, dedicated basis filters that always convolve the image as it comes in. The outputs are multiplied by a set of gain masks, which apply the appropriate interpolation functions at each position and time. The final summation produces the adaptively filtered image. The problem with the Steerable basis filter is that The Kitchen and Rosenfeld, Harris and SUSAN corner detection methods detect noise as false corners and miss some fine features or true corners.

The Harris Corner Detection Method Based on Three Scale Invariance Space: The problems with the traditional Harris corner detector are that it is sensitive to noise an improved three scale. First, three scale spaces with the characteristic of scale invariance were constructed using discrete Gaussian convolution. Then, Harris scale invariant detector was used to extract comers in each scale image. Then, Harris scale invariant detector was used to extract comers in each scale image. Finally, supportable and unsupportable set of points were classified according to whether the corresponding corners in every scale image support that of the original images.

In order to solve the defects with the traditional Harris corner detector is sensitive to scale spaces and noises, an improved three scale Harris corner detection algorithm was proposed[8]. The theory of the scale space is first used to simulate the multi-scale features of images in the computer vision field. Advantages of this method is that the extracted Harris corners from the image after scale zooming were much stable all the same and the characteristics of the corners were not influenced by the change of scales, verifying that the Harris corners extracted by the improved method had the scale invariance. Compared with the scale space on the whole Gaussian pyramid, the utilization factor of the image was increased, the computation time is decreased and the image has high recurrence rate and stability.

Curvature Scale Space Based Image Corner Detection: This paper describes a new method [9] for image corner detection based on the curvature scale space (CSS) representation. The first step is to extract edges from the original image using a Canny detector. The Canny detector sometimes leaves a gap in T-junctions so during edge extraction, the gaps are examined to locate the T-junction corner points. The corner points of an image are defined as points where image edges have their maxima of absolute curvature. The corner points are detected at a high scale of the CSS and the locations are tracked through multiple lower scales to improve localization. The final stage is to compare T-junction corners to CSS corners and remove duplicates. This method is very robust to noise and we believe that it performs better than the existing corner detectors.

CSS Corner Detection Method: The corners are defined as the local maxima of the absolute value of curvature. At a very fine scale there exists many such maxima due to noise on the digital contour. As the scale is increased, the noise is smoothed away and only the peaks corresponding to the real corners remain. The CSS corner detection method finds the corners at these local maxima. The problem is to find the right scale where the corners are to be detected. There are local maxima on the evolved contours due to rounded corners. These can be removed by introducing a threshold value. The curvature of a sharp corner is higher than that of a rounded corner. There is one final addition to the corner candidate declaration. Each local maximum of curvature is compared to its two neighboring local minima. The curvature of a corner point has to be 2 times higher than the curvature of a neighboring extreme. This is necessary since if the contour is continuous and round, the curvature values are well above the threshold value and false corners would be declared.

Curvature Scale Space Corner Detector with Adaptive Threshold and Dynamic Region of Support: Corners play an important role in object identification methods used in machine vision and image processing systems. Single-scale feature detection finds it hard to detect both fine and coarse features at the same time. On the other hand, multi-scale feature detection is inherently able to solve this problem. This paper proposes an improved multi-scale corner detector with dynamic region of support [10], which is based on Curvature Scale Space (CSS) technique. The proposed detector first uses an adaptive local curvature threshold instead of a single global threshold as in the original and enhanced CSS methods. Second, the angles of corner candidates are checked in a dynamic region of support for eliminating falsely detected corners. The proposed method has been evaluated over a number of images and compared with some popular corner detectors. The results showed that the proposed method offers a robust and effective solution to images containing widely different size features. Among the corner candidates, although some points are detected numerically as the local absolute maximum, the measurable differences in curvature between this maximum and its neighbors in the region of support are often very small. This is the case of rounded corners and fortunately we can remove them by using an adaptive local curvature threshold. In principle, we set the threshold for a candidate according to its neighborhood region's curvature. The local maxima whose absolute curvatures are under its local threshold are eliminated.

Image Corner Detection Based on Curvature Scale Space (CSS) and Adaptive Thresholding: The basic problem in the corner detection [11] is that it can't be able to detect fine and coarse features of an image at the same time using single scale corner detection. In order to overcome the problems multi-scale image corner detection method is used which is based on curvature scale space. They are also fixing adaptive threshold in the image. An adaptive local thresholding is used instead of global thresholding. To eliminate falsely detected corner, the angles of corners are checked in a dynamic region of support. The CSS technique is suitable for recovering invariant geometric features of a planar curve at multiple scales. It is very important in defining the angles.

In this algorithm the curvature is fixed at a low scale on all the contour to get all true corners. In the next step all of the curvature local maxima are considered as corner candidates, including the false corners then by using adaptive thresholding value and true corner angles the false corners are eliminated. Fixing the thresholding value is very important as they set it according to the neighborhood region's curvature.

Multi-scale Curvature Product for Robust Image Corner Detection in Curvature Scale Space: The corner detection is done through scale multiplication [12] and it starts with extracting the contour of the object of interest, using a Gaussian derivative filter which computes the curvature of contour at various scales. Local extremes of the product of the curvatures at different scales are reported as corners when the value of the product exceeds a threshold. Apart from the traditional curvature scale-space, this algorithm is improved in two ways: first, it takes fine scale as the scale product. There is no need to go for coarse-to-fine corner tracking. Second, since many scales are involved there is no way of differentiating from false corner to negative corner with a single threshold.

For this, a concept of corner detector has to be defined, which is robust, simple and should be effective. They denote a Gaussian function dilated by a scale factor.

The multi-scale curvature product indicates that corners present observable magnitudes along the scales, while magnitudes of the noise decrease rapidly. The curvature orientation of corners propagates at different scales while that of non-corners randomly change.

A robust, simple and effective corner detector can be obtained. The corner is directly determined as the local maxima after global thresholding. Curvature products are always greater, than one of the non-corners, the threshold can be easily found out. The detection and localization performance analysis of the scale product are performed by two ways: consistency of corner numbers(CCN) and accurate(AUC). Many images were taken and they were measured in rotation, uniform scaling, non-uniform scaling and affine transforms. The most significant property of the scale product is effectively enhancing curvature extreme peaks while suppressing noise and improving localization, Experiments also demonstrate that the method has the results of good quality and robustness to noise with only a low computational cost.

A Robust Css Corner Detector Based on the Turning Angle Curvature of Image: A new contour based corner detection [13] method is presented based on the turning angle curvature processed through the contour gradients of the image. Normally curvature is processed through the pixel locations of the extracted image contours. The image gradient information are already computed in most contour extraction methods. This algorithm makes use of the available gradient information to compute the curvature function and take local extremums as potential corner candidates. Using the validation and iterative square algorithm local geometric structure of the contour are approximated. In general, curvature is defined as the amount by which a curve deviates from being straight, another way to define curvature is by taking the difference between tangents of consecutive points, which is called the turning angle curvature. Finding the turning angle curvature is usually easier because a contour detector computes the gradient magnitudes at each pixel of an image during edge detection. By using the horizontal and vertical gradient information, the tangent is obtained. To get the curvature response of the extracted angle values, relative angle variations for the consecutive gradient vectors are computed. If the tangent estimation of the consecutive contour elements is considered to be a function of time, then the angle changes along the contour with respect to time. Once the turning angle curvature is computed, all corner candidates are detected as the local maximas of the curvature which are larger than a certain global threshold. Finally, the detected corner candidates are validated. Most of the corner validation algorithms are based on the curvature function. However, curvature function can easily be corrupted due to noise and Gaussian scale convolution process. In all the existing algorithm they use curvature information to validate the corners, the proposed method validates the corners with respect to the geometric structure of the contour. After finding all the corners, approximation is done by fitting to lie segments with an iterative least square estimation procedure. A least squares error threshold are validated and tried to fit lines to the neighbour pixels of the corner candidate until the fitting error exceeds the threshold.

Multiscale Corner Detection for Gray Level Images Using Plessey Corner Detection: Plessey corner detector is known for its good performance. But, Plessey operator has three disadvantages: it works only in the spatial domain, so it can only detect corners in specific scale but the proposed detector works in the scale-space domain so it can detect corners belonging to different scales, three parameters are needed to be set manually in the original Plessey method, while the proposed method ensures to set only one parameter and the delocalization is a well-known inherent problem for the Plessey corner operator. The proposed algorithm partially solves this problem by detecting the corners from smaller scale to larger scales [14].

Scale-space Based Corner Detection of Gray Level Images Using Plessey Operator: A new multi-scale corner detection method [15]is proposed for gray level images based on scale-space theory and Plessey corner detection algorithm. The proposed algorithm works in the scale-space domain so that it detects corners belonging to different scales instead of certain scale, one parameter needs to be set instead of three parameters and delocalization. The proposed algorithm solves the problem by detecting the corners from small scale to large scale, then track back from large scale to small scale. As the delocalization in the smallest scale can be ignored, the proposed method obtains the accurate localization. The Plessey corner detector is robust to noise because it uses only the first derivative of the image and is smoothed by a circular Gaussian kernel. Plessey operator has a good isotropic response and it's very easy to implement. We have also lot of problems in Plessey operator mentioned. So to overcome this problem We set a range of scales from small to large. The image is transformed into the scale-space domain. At each scale compute the first order derivatives, smoothen it along the horizontal and vertical direction. After detecting the local maxima by thresholding, commonly used post-processing algorithm non-maximum suppression need be applied to suppress the multi-responses. When the corner detection is finished at all the scales, the final result is obtained by combining the corners detected at every scale. Lastly, a tracking back algorithm is applied to get the accurate localization. For each detected corners, we search for its corresponding local maxima in its neighborhood from large scale to small scale. Consequently, the accurate localization is obtained at the first scale, *i.e.*, the smallest scale.

Optimizing the Susan Corner Detection Algorithm for a High Speed Fpga Implementation: As the original SUSAN algorithm performs poorly on non-synthetic images, SUSAN algorithm is well improved in to detect the images corners and is a contribution of real-time FPGA implementation of feature detector. SUSAN is an abbreviation for 'Smallest Univalue Segment Assimilating Nucleus' implementing on FPGA is relatively low computational complexity [16]. Apart from adders and subtracts no complex mathematical operations (e.g. multipliers) are necessary. Corner detectors were divided into 2 parts: first, determination of the univale segment assimilating nucleus. Second, search image for local minima which indicate corner in the original image. The SUSAN area is calculated by placing a circular mask around a pixel R_0 and comparing its brightness to that of each pixel r in the mask. If the brightness is similar to those of the pixels which is in the same segment then it lets to problem. So, the SUSAN area is increased by one.

A Modified Susan Corner Detection Algorithm Based on Adaptive Gradient Threshold for Remote Sensing: In remote sensing image registration plays an important role in image processing. In image registration corner detection is a vital role. SUSAN algorithm is enhanced with adaptive gradient threshold ensuring the gray threshold automatically [17]. In the SUSAN algorithm two threshold values are very important, one is the geometric threshold and another is gray difference threshold. The geometric threshold g decides the sharp degree of corner detection. The smaller the threshold, the sharper is the corner.

Based on boundary extraction $g = \frac{3}{4}\, n_{max}$

Based on corner detection $g = \frac{1}{2}\, n_{max}$

Usually, a good result could be obtained without adjusting. Gray difference threshold *t* determines the ability that the SUSAN operator could detect the points which are smallest contras and removal of noise. The SUSAN operator could detect the points which are smallest contras and removal of noise. In fact, an image contains lots of feature points, it's unnecessary to choose all of the points, or the computing time will be longer. Here it is mainly controlled by changing the threshold t. This algorithm which helps us to easily change the t. Hence, this paper gives an adaptive extraction method for this t. Aa circular mask which contain 37 pixel which can have the radius3.4 pixels. The gray difference between the center pixel and each pixel in mask for every pixel is calculated in SUSAN mask.

Study of Improving the Stability of Susan Corner Detection Algorithm: Smallest Univalue Segment Assimilating Nucleus (SUSAN) [18] is one of the most excellent methods which is robust to noise and less affected by rotation. However, it could not detect all the true corners and generate some false corners in some special case. To solve these problems, an improved SUSAN corner detector is proposed and its performance is compared with SUSAN corner detection. With the improved SUSAN, a corner point is judged based on gray level values of the pixels in a circular neighborhood of the nucleus which is the same as the conventional SUSAN, however, the improved SUSAN calculates the number of the pixels in the univalue adjoining nucleus and connected segment rather than calculate the number of the pixels of univalue nucleus in the neighborhood. Due to this improvement, the improved SUSAN can not only inherit the main merits but also avoid the fatal fault of conventional SUSAN. Experimental results have demonstrated that the improved SUSAN corner detection is accurate and efficient.

The point under the examination is called the nucleus. A corner value which is detected through the grey level values of the pixels in a neighborhood of the nucleus. They are using a circular mask in the center of the nucleus. In the pixels with approximately the same brightness as the nucleus are grouped and the area formed by it is the USAN (univalue segment assimilating Nucleus). The USAN reaches the maximum when the nucleus lies in a flat region of the image surface. It falls to the half of the maximum when the nucleus is on straight edge and falls even further when the nucleus is a corner. The local minima of the USAN.

The SUSAN algorithm has the advantages of being robust to noises and rotation of the image because its mask is circular and used statistic method to count univalue points. However, this algorithm may generate false corners and miss some corners in some special situation. This method adopt it's merit and used a circular mask with the center at the nucleus and counted univalue points with statistic method. To the shortcoming of the SUSAN, the improved SUSAN calculates the number of the pixels in the univalue adjoining nucleus and connected segment rather than calculating the number of the pixels of univalue nucleus in the neighborhood.

Analysis and Improvement of SUSAN Algorithm: A modified Smallest Univalue Segment Assimilating Nucleus (SUSAN) algorithm [19] based on the local gray value character of an image is presented here. Beginning with an explanation of the principle of edge detection and noise reduction, it is found that SUSAN algorithm is immune to all noise points but the isolated noise points. To improve this, an original edge response formulation is optimized by imposing constraint conditions. Then a set of anti-noise tests were run to compare the scheme with the original algorithm and other popular edge detectors. The results show that for Gaussian noise and salt-and-pepper noise, the improved SUSAN algorithm performs much better than the original one in view of sensitivity to noise and detection of edges and especially for salt-and-pepper noise the improved SUSAN algorithm works best among the all detectors tested here. Considering noise points differ quite a lot from its neighboring points in intensity. Thus, the value S of noise points is much lower than that of other pixels. For this reason, it should be easy to pick out the noise points. Unfortunately, they tend to be recognized as edge points.

Fast Susan Edge Detector by Adapting Step-Size: The SUSAN algorithm [20] is a popular edge detector for its high localization precision, noise-robustness and good connectivity at junctions. Straightforward implementation of SUSAN edge detector is performed by sliding a circular mask pixel by pixel on an image. For each pixel in the raster scan order, the neighbor pixels in the circular mask around it are taken and used to compute the USAN area, according to which whether the current pixel is an edge point or not is judged. However, redundant computation exists in the direct implementation of SUSAN edge detector because of the pixel-by-pixel sliding way of the circular mask, which makes it somewhat inefficient. A fast implementation of SUSAN edge detector was propose to decrease the redundancy. Instead of sliding the mask by one pixel every time, an adaptive type of raster scan referred to as adaptive sliding mask which adjusts the sliding step-size adaptively according to USAN area is proposed.

The proposed ASM-SUSAN edge detector improves the efficiency by sliding the mask adaptively instead of only one pixel at a time. This idea is depicted in the step-size changes adaptively based on the place where it lies: near a region boundary, it becomes small, one pixel at least; in a homogeneous region, it becomes large, R at most. Whether the nucleus lies near an edge or in a homogeneous region can be simply determined by the already computed USAN information without adding extra quantity. Now the remaining question is how to correlate the adaptive step-size to USAN of the current nucleus. In other words, it is necessary to establish an appropriate mapping between adaptive step-size and USAN of the current nucleus. A better solution would be to examine for each nucleus the size of USAN area as well as the distribution of USAN (like shape, direction, etc.) and to determine step-size in [1, R] based on the distance from the nucleus to the boundary between USAN and non-USAN which usually corresponds to edges. Such a mapping requires high computational resources, however and may trade off the gain in speed by sliding the mask adaptively.

An Improved Corner Detection Algorithm Based on Chain-coded Plane Curves: Corner can be measured on chain-coded curves which is the product of the length of the uniform chain sections to either side of a point, times the angle of discontinuity of that particular point. It is well close to the expectation of the human on corner detection. Here, it averages multiple values to avoid the selection of spurious corners. To determine the forward and backward arm end point the algorithm uses a maximum cut off values [21].

At some point, the cornerity point tends to have smaller value when they are being used. The algorithm will detect spurious forward arm when s value is 5 which leads to a comparatively smaller cornerity value. Humans would see only one corner as having both long forward and backward arms modified algorithm uses the approach of averaging the K values obtained at a particular point for multiple values. When determining these lengths, the modified algorithm will limit the t values to some fraction of the number of nodes in the given image. The purpose of this modification is to reduce the cornerity (or the K values) of spurious nodes with long forward and backward arms. Setting such a limit to arm length is more in accord with human perception of corners, which depends on object size.

Corner Detection on Digital Curves Based on Local Symmetry of the Shape: A new method is used for detecting corner based on local symmetry of the shape. This method consists of two steps: computation of symmetry measure for symmetry relative to line at every point on a digital curve and the location of reasonable local maxima of the symmetry measure as corners. The results are verified with different digital curves which achieved better results. The method proposed in [22] is a fundamental idea that the corners locate at the points on a curve where the symmetry measures are local maxima. The symmetry measure just appears as an impulse in local maximum. In the middle of the consecutive corners, a local maximum appears again just as the top of the roof. This procedure is good to make local maxima remarkable. Corners of the digital curve C can be detected via the use of symmetry measure calculated on the augmented curve. It should be noticed that the local maximum corresponding to a corner does not appear as an idealized impulse. In order to identify local maxima corresponding to corners and to locate the corner points the following the procedure is used which consists of two steps: finding local minima of the symmetry measure on C, dividing the augmented curve t~ into the intervals and computing the mean slope of symmetry measure for each interval and discriminating the intervals and identifying the corners.

Corner Detection for Chain Coded Curves: This algorithm is mainly proposed [23] to improve the performance of the existing algorithm. The new algorithm measures the number of links to either side of a point that can produce a large straight line. The digital straight line value which is used as an indication of curvature at that point is the corner. The improved algorithm which can also reduce the false corner detection.

The chain coded representation of a boundary with a corner (*i.e.* a point of infinite curvature) cannot be distinguished from that of a boundary with very high curvature. When detecting corners from chain coded, the very high curvature and the corners in the image will be detected. Due to high curvature there will be tradeoff between true corner and the false corner. Chain coded contours the curvature at a point is related to the expected length of the maximal digital straight line around that point. Digital straight line lengths are used around the point of indication of the curvature at that point. An indication of low curvature exists if the straight line distance is large while a small distance is indicative of high curvature. Detection of corners is more difficult when the objects are not very large. The focus here is on this more difficult case for which a low threshold of straight line distance is used to detect corners.

Fast Corner Detection: A new algorithm is proposed to compute the intensity change in arbitrary direction interpixel approximation is used. In order to reduce the computational cost and time, a multigrid approach is used and it is also used to improve the quality of the detected corners [24]. All the corners are categorized into geometrical and texture corners. Geometrical corners belong to the boundaries of the object in the scene. The objects are always expected to be small in size and few in number comparing to the number of pixel in the image scene do not vanish or change shape on lower scales, geometrical comers are relatively invariant to the scale (they will disappear at sufficiently low scale) or the window used to compute the CRF. These corners can be detected at higher scales. Texture corners are associated with small or textured objects in the scene and the physical corners of the image are not taken into account. So they are not good enough in matching two images because of these reason we do not find texture corners.

Analysis of Gray Level Corner Detection: Here, the analysis of gray level corner detection [25] has been carried out. The performance of variouscornerness measure are done through the performance of robustness detection, localization, stability and complexity. The differential features of the image surface of thesecornerness is analyzed and measured. They used a new method called gradient-direction corner detector for corner detection which is developed from the popular Plessey corner detection. The gradient-direction corner detector is based on the measure of the gradient module of the image gradient direction and the constraints of the false corner response suppression. Only the negative minimum of the cornerness measure exists. The corner detector is sensitive to the noise effects. Even worse, it falsely detect the edge points on which one principal curvature is large and the other principal curvature's magnitude fluctuates significantly with noise. Due to the rounding effect, the detected corner points are not well localized near the corners, especially when the edge near the corner is blurred. The corner detector does not detect consistently the same corner points from one image to the next and thus it is instable. The corner detector algorithm only needs to decide the thresholding value.

The zero of the derivative of the measure of cornernessinclude two kinds of points: positive maximums and negative minimums. There are falsely detected negative minimums in the straight oblique line, especially when the edge is strong and noise-effected. The positive maximum of Beaudet corner detector can well detect the corner point, but they are some sensitive to noise. The positive maximum of Beaudet corner detector does not correctly locate the corner point, they are not stable in the scale space.

The performance of gradient-direction corner detection is slightly inferior to that of the Plessey detector but the performance of localization is better than that of the Plessey detector ± balance between the performance of detection and the localization. The corner detector is instable because of the application of constant-variable false corner response suppression. The corner detector algorithm needs to decide the thresholding value and the variable K Plessey for the false corner response suppression ± one less parameter than the Plessey corner detector. The corner detector algorithm only requires $M^2(4N^2+ 8)$ operations where the image is M by M, the neighborhood of the gradient operators is N2 ± simpler than the Plessey corner detector.

A Local Edge Detector Used for Finding Corners: The corner detectors are mainly based on the edge detectors. The corners are extracted with the use of the edge points. A local edge detection algorithm [26] is proposed that can be used well in corner detectors. They detect corners locally based on both gradient magnitude threshold and gray level analysis. The process is dynamic and can provide correct edge points for detecting corners. The problem in finding corners is simplified into detecting simple lines in a local coordinate system. Hough transform is modified to organize the edge points generated by the new edge detector into simple lines. It is proved that the new corner detector based on the local edge detector works well over most images.

All the window is treated as a local coordinate system, with the central pixel being the origin. If the central pixel is a corner point it has to satisfy two conditions: under certain edge measurement, its edge response should be large enough, as corner point should also be an edge point and at least two straight lines passing through it should be detected, i.e that is two simple lines should exist. Instead of marking edge points globally, they are detected locally based on both gradient magnitude threshold and gray level analysis. The process is dynamic and can provide correct edge points for detecting corners.

Multiscale Contour Corner Detection Based on Local Natural Scale and Wavelet Transform: The corner candidates corresponding to wavelet transform modulus maxima (WTMM) [27] at different scales are used. The points corresponding to wavelet transform modulus maxima (WTMM) at different scales are taken as corner candidates. For each corner candidates, the scale at the maximum value of the normalized WTMM that exists is defined as its “local natural scale” and the corresponding modulus is taken as its significance measure which gives the accurate measure of the corner candidates. The proposed method works well in the short contour and long contour.

The dyadic WT is applied to the orientation function to estimate the curvature at all possible scales because no scale should be got without prior information. The points with the WTMM are taken as corner candidates. Here the corner depends on the relative conception, it depends on the shape and scale considered in the detection. At some specific scales opntusecandidates will not be considered if there exists acute candidates. Therefore it is necessary to normalize the values of the WTMM at each scale. For different candidates at the same scale, the candidates with acute angles produce large WTMM, while the candidates with obtuse angles have small WTMM. For each candidates with different scales the value of the normalized WTMM at certain scale represents the cornerity of the candidates and the maximum value of the WTMM shows the stronger cornerity at corresponding scale. Consequently, the scale at which the maximum value exists should be defined as its ‘‘local natural scale’’ and the corresponding maximum modulus is taken as the significance measure.

RESULT DISCUSSION

Harris corner detector in the front runner in these detection techniques gives us the highest percentage of corner detection. It efficiently helps in finding difference between the true corner and false corners other corner detectors lack a bit in this thing. They are also using filters to and other bilateral things to do this. Thus the Harris corner detector is vulnerable to noise but it can be also eliminated by using some filters. The main disadvantage of Harris corner detector is which consumes lot of time to detect the corners if we use some technique to reduce the computational cost then this technique become handy. In curvature scale space (css) we are using different scales to detect the corners using multi-scale this is very helpful in detecting the corners. But the problem here is it can’t work as efficient as Harris corner detector. Then contour based detectors which helps to reduce the computational cost a lot but in other aspects which has a very low profile.

CONCLUSION

All the corner detection technique has its own advantages and disadvantages in its own way of differentiating which is better and worst is difficult. We can just go for the efficiency detection of each algorithm and check which one is better in this survey. Harris corner detection and improved Harris corner detection algorithm has a better efficiency then the other corner detectors. It is handy if any one of Harris corner detectors is chosen and enhanced.

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