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SURVEY ARTICLE

PERFORMANCE EVALUATION OF CORNER DETECTORS: A SURVEY

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Abstract— An image may contains number of important features, such as closed-boundary regions, edges, contours, line intersections, Corners, etc. Among them corner is one of the important feature, which can be identified by the change of intensity gradient in at least two-directions. Corner detectors have many applications in computer vision, object tracking or recognition. The corner detectors are classified into three clauses: contour based, intensity based and parametric based model. The performances of corner detector are presented in terms of consistency, accuracy, matching score, information rate, ground truth, visual inspection. The objective of this paper is to provide a comprehensive study of corner detection methods and their evaluation.

Key words— corner; intensity gradient; repeatability; consistency; matching score; ground truth

I. INTRODUCTION

Two images can be related by matching locations in the image that are in some way interesting. Such points are referred to as interest points and are located using interest point detectors. 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. These points are located using corner point detectors. Corner detectors have many applications in computer vision and object recognition or tracking.

II. TYPES OF CORNER DETECTORS

A wide variety of interest point and corner detection algorithms exist and these methods can be divided in to three main clauses: contour based, intensity based and parametric model [15, 17]. Contour based first extract contours and then search for maximal curvature or inflexion points along the contour chains, or does some polygonal approximation and then search for intersection points. Intensity based methods estimate a measure which is intended to indicate the presence of a corner directly from the image grayvalues. Parametric model methods fit a parametric intensity model to the signal. They often provide sub-pixel accuracy, but are limited to specific types of interest points, for example to L-corners. In the following sections, we present corner detection methods for each of those categories.

A. Contour based methods

Asada and Brady [1] extract points for 2D objects from planar curves. They observe that these curves have special characteristics: the changes in curvature. These changes are classified in several categories: junctions, endings etc. To achieve robust detection their algorithm is integrated in a multi scale framework. Arrebola et al. introduced different corner detectors based on local and circular histogram of contour chain code. Horaud et al extract line segments from image contours. These segments are grouped and intersections of grouped line segments are used as interest points. Zhan g and Zhao considered a parallel algorithm for detecting dominant points on multiple digital curves. Shilat [2] et al first detects ridges and troughs in the images. Interest points are high curvature points along ridges and troughs, or intersection points. They argue that such points are more appropriate for tracking, as they are less likely to lie on the occluding contours of an object. Mokhtarian and Suomela [3] describe an interest point detector based on two sets of interest points. One set are T-junctions extracted from edge intersections. A second set is obtained using a multi-scale framework: interest points are curvature maxima of contours at a coarse level and tracked locally up to the finest level. The two sets are compared and close interest points are merged.

B. Intensity based methods

Kitchen and Rosenfeld [4] computed a cornerness measure based on the change of gradient direction along an edge contour multiplied by the local gradient magnitude as follows:

$$C_{KR} = \frac{I_{xx} I_y^2 - 2 I_x I_y I_{xy} + I_{yy} I_x^2}{I_x^2 + I_y^2}$$

The local maximum of this measure isolated corners using a non-maximum suppression method applied to the gradient magnitude before its multiplication with the curvature. This detector is sensitive to noise and shows poor localisation. Plessey cornerness measure is

$$C_P(x, y) = \frac{\left\langle I_x^2 \right\rangle + \left\langle I_y^2 \right\rangle}{\left\langle I_x^2 \right\rangle \left\langle I_y^2 \right\rangle + \left\langle I_x I_y \right\rangle^2}$$

where I_x and I_y were found using the (n · n) first-difference approximations to the partial derivatives and calculated $I^2{}_x$, $I^2{}_y$, and I_xI_y, then applied Gaussian smoothing, and computed the sampled means $(I^2{}_x)$, $(I^2{}_y)$, and (I_xI_y) using the (n x n) neighbouring point samples. This algorithm suffers from sensitivity as it depends on second order derivative terms, and it also provides poor repeatability and localization. Chabat et al. introduced an operator for detection of corners based on a single derivative scheme introduced in by Yang et al. Zheng et al., proposed a gradient-direction corner detector that was developed from the Plessey corner detector. Moravec [5] observed that the difference between the adjacent pixels of an edge or a uniform part of the image is small but at the corner the difference is significantly high in all directions. Beaudet [6] proposed a determinant operator which has significant values only near corners. Dreschler and Nagel [7] used Beaudet's concepts in their detector. Lai and Wu considered edge-corner detection for defective images. Tsai proposed a method for boundary-based corner detection using neural networks.

Smith and Brady [8] introduced the SUSAN algorithm as follows: consider an arbitrary image pixel and the corresponding circular mask around it (the centre pixel shall be called the nucleus). If the brightness of each pixel within a mask is compared with the brightness of that mask's nucleus then an area of the mask can be defined which has the same (or similar) brightness as the nucleus. This area of the mask shall be known as the "USAN", an acronym standing for "Univalue Segment Assimilating Nucleus" and the smallest area of is called as SUSAN (Small Univalue Segment Assimilating Nucleus). To find corners, they computed the area and the centre of gravity of the USAN, and developed a corner detector based on these parameters.

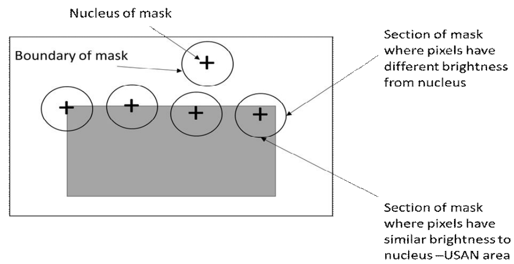


Fig 1: SUSAN principle

C.Harris and M.J.Stephens [9] proposed a corner detection algorithm in which the corner point is determined with the variation of gray value in a small window whose size is determined by the actual situation. A point is not detected unless the gray value changes in both *x* and *y* direction. The variation of the gray value is

$$E(u, v) = \sum w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

I(x, y) is the gray value of the point whose coordinates is (x, y). (u, v) is window moving distance in x and y direction. W(x, y) represents the window.

Trajkovic and Hedley [10] proposed a corner point matrix, it generates two corner points matrix first, and then determines which position is the best match position by maximizing the number of corner points overlapped between two corner points matrix.

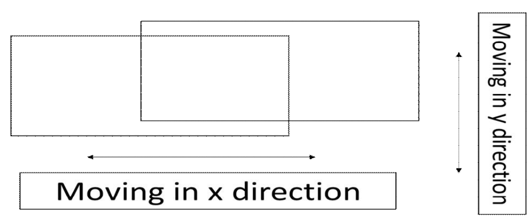


Fig 2: Fast corner detector principle

Kanade-Lucas-Tomasi [11] proposed a corner detector which operates by comparing a patch of image information in 2 consecutive frames of an image sequence. It assumes that images taken at near time instants are usually strongly related to each other, because they refer to the same scene taken from only slightly different viewpoints.

C. Parametric model based methods

The parametric model used by Rohr [12] is an analytic junction model convolved with a Gaussian. The parameters of the model are adjusted by a minimization method, such that the template is closest to the observed signal. In the case of an L-corner the parameters of the model are the angle of the L-corner, the angle between the symmetry axis of the L-corner and the x-axis, the grey values. The position of the point and the amount of blur. Positions obtained by this method are very precise. However, the quality of the approximation depends on the initial position estimation. Rohr uses an interest point detector which maximizes det (A) as well as the intersection of line segments to determine the initial values for the model parameters. This matrix A averages derivatives of the signal in a window around point (x, y):

$$A(x, y) = \begin{pmatrix} \sum_{(x_k, y_k) \to W} (I_x(x_k, y_k))^2 & \sum_{(x_k, y_k) \to W} I_x(x_k, y_k) I_y(x_k, y_k) \\ \sum_{(x_k, y_k) \to W} I_x(x_k, y_k) I_y(x_k, y_k) & \sum_{(x_k, y_k) \to W} (I_y(x_k, y_k))^2 \end{pmatrix}$$

Where I(x, y) is the image function and (x_k, yk) are the points in the window W around (x, y). This matrix captures the structure of the neighbourhood. If this matrix is of rank two, that is both of its eigenvalues are large, an interest point is detected. A matrix of rank one indicates an edge and a matrix of rank zero a homogeneous region. Deriche and Blaszka [13] develop an acceleration of Rohr's method. They substitute an exponential for the Gaussian smoothing function. They also show that to assure convergence the image region has to be quite large. In cluttered images the region is likely to contain several signals, which makes convergence difficult. Baker et al propose an algorithm that automatically constructs a detector for an arbitrary parametric feature. Each feature is represented as a densely sampled parametric manifold in a low dimensional subspace. A feature is detected, if the projection of the surrounding intensity values in the subspace lies sufficiently close to the feature manifold. Furthermore, during detection the parameters of detected features are recovered using the closest point on the feature manifold.

III. PREVIOUS CRITERIA FOR PERFORMANCE EVALUATION

There are many methods for performance evaluation of corner detectors, but until now no standard evaluation method has been developed for these criteria so results vary based on how the different criteria is tested. The existing evaluation methods are: ground-truth verification, visual inspection, localization accuracy, consistency, repeatability, information rate, accuracy, theoretical analysis and specific tasks.

A. Ground truth verification

Ground truth is generated by human judges, and can be used to determine the undetected features (false negatives) and the false positives. Bowyer et al. [14] used human generated ground truth to evaluate edge detectors. Their evaluation criterion is the number of false positives with respect to the number of unmatched edges which is measured for varying input parameters. Structured outdoor scenes such as airports and buildings were used in their experiments.

B. Visual Inspection

Methods using visual inspection are even more subjective as they are directly dependent on the human evaluating the results. L´opez et al. (1999) define a set of visual criteria to evaluate the quality of detection. They visually compare a set of ridge and valley detectors in the context of medical images. Heath et al. (1997) evaluate detectors using a visual rating score which indicates the perceived quality of the edges for identifying an object. This score is measured by a group of people. Different edge detectors are evaluated on real images of complex scenes.

C. Information rate

Information content is a measure of the distinctiveness of an interest point. Distinctiveness is based on the likelihood of a local grey value descriptor computed at the point within the population of all observed interest point descriptors. Given one or several images, a descriptor is computed for each of the detected interest points. Information content [17] measures the distribution of these descriptors. If all descriptors lie close together, they don't convey any information i.e. the information content is low, as any point can be matched to any other. On the other hand if the descriptors are spread out, information content is high and matching is likely to succeed. Information content of the descriptors is measured using entropy. The more spread out the descriptors are, the higher is the entropy.

D. Localization Accuracy

Localization accuracy is the criterion most often used to evaluate interest points. Localization refers to how accurately the position of a corner is found. Farzin Mokhtarian, Farahnaz Mohanna [15] proposed the criterion of accuracy is defined as

$$ACU = 100 \times \frac{\frac{N_a}{N_o} + \frac{N_a}{N_g}}{2}$$

Where ACU stands for accuracy. The value of ACU for accurate corner detectors should be close to 100%. Note that if a corner detector finds more false corners which implies more matched corners, it does not follow that the ACU of this detector is high since in this case, if N_a/N_g is near one, N_a/N_o drops closer to zero. On the other hand, if a corner detector finds less corners which means less matched corners, N_a/N_o goes to one and N_a/N_g drops closer to zero. Therefore in both cases, the ACU of such detectors computed through the above Equation is less than 100%. Note that the case of $N_o = 0$ in Equation occurs if a test image has no corners or the test corner detectors cannot detect any corners.

E. Theoretical analysis

Methods using this approach study the behaviour of feature detectors using theoretical feature models. However, such methods are limited since they are applicable only to very specific features. Examples follow: Deriche and Giraudon studied the behaviour of three corner detectors using an L-corner model. Their study allows them to estimate the localization bias. Rohr also carried out a similar analysis for L-corners with aperture angles in the range (0–180).

F. Evaluation based on specific tasks

Edge detectors have occasionally been evaluated through specific tasks. The reasoning is that feature detection is not the end goal but only the input for further processing. Hence, the best performance measure is the quality of the input it prepares for the next stage. While this argument is correct to some extent, evaluations based on a specific task and a specific system are difficult to generalize and therefore of limited value. An example of this approach is that of Shin et al. [16] in which a number of edge detectors were compared using an object recognition algorithm.

G. Consistency

Consistency means corner numbers should be invariant to the combination of noise, rotation, uniform or non-uniform scaling and affine transform. By noise we mean naturally occurring noise in images such as camera noise and discretization errors. Farzin Mokhtarian, Farahnaz Mohanna [15] defined criterion of consistency of corner numbers as follows:

$$CCN = 100 \times 1.1^{-|N_t - N_o|}$$

Where CCN stands for consistency of corner numbers. Since consistent corner detectors do not change the corner numbers from original image to transformed images then the value of CCN for stable corner detectors should be close to 100%. Any differences between the number of corners in the original image (N_o) and the number of corners in the transformed image (N_t), causes CCN to drop below 100% as $|N_t \_ N_o|$ grows larger. CCN is close to zero for corner detectors with many false corners. Note that we studied different formulae carefully, and chose an exponential form as the most suitable one since it always maps the CNN value to the [0–100%] range.

IV. EXPERIMENTAL RESULTS

In this paper we used repeatability and matching score as a criterions for the performance evaluation of corner detectors or interest point detectors. So, the detectors having good repeatability rate (good stability) and matching score is considered as good corner detector. The below shown figures are used for performance evaluation of corner detectors

(a) (b)

Fig 3: Test image pairs (building)

A. Repeatability

The repeatability rate is defined as the number of points repeated between two images with respect to the total number of detected points.

$$Repeatability = \frac{Tentativematches}{\min(n_1, n_2)}$$

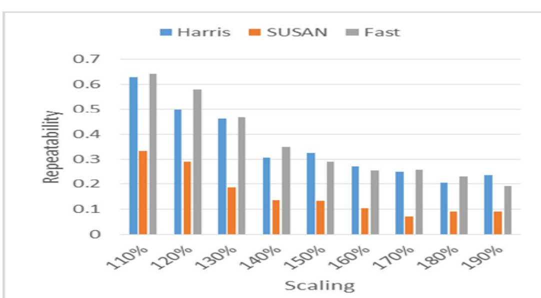
Where n_1, n_2 are the no. of corners of test image pair respectively. To measure the number of repeated points, we have to take into account that the observed scene parts differ in the presence of changed imaging conditions, such as image rotation or scale change.

B. Matching Score

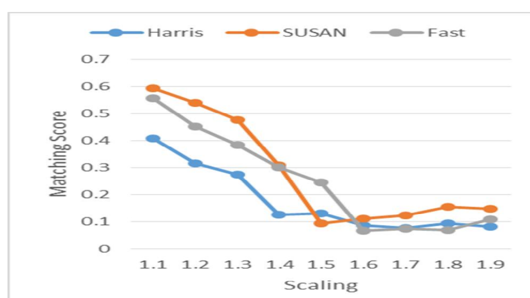
The measure of matching is computed between the two test image pairs and the matching score is computed as follows

$$\text{Matching Score} = \frac{\text{Correct matching points}}{\text{Total matching points}}$$

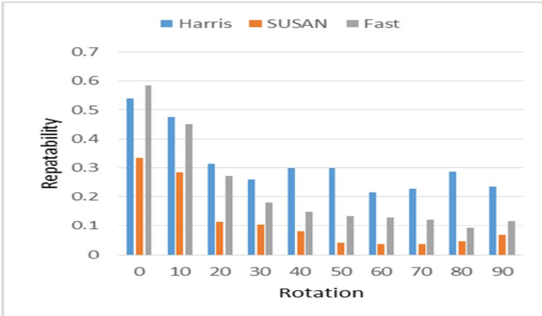
The matching score is computed on test image pair with a gradual increase in transformation (rotation and scaling). The results of repeatability and matching score for transformation of test image (rotation and scaling) is given below



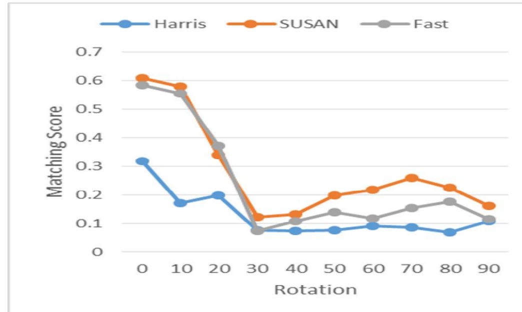
(a)



(c)



(b)



(d)

Fig 4 :Repeatability rate (a) Scaling (b) Rotation Matching Score (c) Scaling (d) Rotation

Fig.4 (a) shows Harris and fast gives equal and good performance in scale change from 110% to 190%, The SUSAN stands last. Fig.4 (b) shows repeatability for image rotation. The rotation angles vary between 0 to 90 degrees in steps of 10 degree. Harris detector gives good performance and fast gives the second best performance, the other corner detector SUSAN gives least good performance Fig 4 (c & d) shows SUSAN and fast gives almost equal and good performance in scale change from 110% to 190%, and rotation angles between 0 to 90 degrees. Harris stands last but the earlier detectors degrades matching score drastically by increase in transformation (rotation and scaling) and it is not the case with the latter because the fall is very low

The mosaic experiments are carried out on the test image pair and the obtained image mosaic are given below

Fig 5: Image mosaic results using feature points

The repeatability rate, ,matching score, corners detected, initial matches and correct matches of the considered detectors when applied on the test image pairs are shown in the below table.

Methods	Image size	Number of corners detected	Number of initial matches	Number of correct matches	Repeatability rate %	Matching Score
Harris	Fig3(a) 256X256 Fig3(b) 256x256	259 199	107	38	31.77	0.3177
Fast		463 381	223	104	58.29	0.6076
SUSAN		1775 1568	525	319	60.76	0.5829

TABLE 1: IMAGE MOSAIC RESULTS

V. CONCLUSION

This paper provided some important information about the existing corner or interest point detectors. The majority of published corner detectors have not used properly defined criteria for measuring the performance of their corner detectors. They have only demonstrated their results on different images in comparison to other corner detectors. So, performance evaluation of selected corner detectors is also done using repeatability and matching score as a criterions.

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