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# A model-based approach to junction detection using radial energy

Eric D. Sinzinger\*

Department of Computer Science, Texas Tech University, Lubbock, TX 79409-3104, USA

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#### **Abstract**

A novel junction detector is presented that fits the neighborhood around a point to a junction model. The junction model segments the neighborhood into wedges by determining a set of radial edges. The radial edges are invariant to affine transforms, creating an affine invariant junction detector.

The radial edges are evaluated based upon the pixels along the edge. The angle between the pixel gradient and the vector to the potential junction point forms the initial basis for the measurement. An initial set of radial edges is selected based upon identifying local maximums within a given arc distance. An energy function is applied to the resulting radial segmentation, and a greedy optimization routine is used to construct the minimal set of radial edges.

To identify the final junctions, a second energy function is used that combines the components of the first energy function with the resulting change in standard deviation by separation into radial segments. The junctions with the most energy in their local neighborhoods are selected as potential junctions. The neighborhoods about the potential junctions are analyzed to determine if they represent a single line or multiple non-parallel lines. If the neighborhood represents multiple non-parallel lines, the point is classified as a junction point.

The junction detector is tested on several images including both synthetic and real images. Highlights of radially segmented junction points are displayed for the real images.

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#### 1. Introduction

Detection of local features is an essential low level vision task for many computer vision operations including matching, tracking and recognizing. There has been a great deal of research in the past 30 years on local feature detection to derive an algorithm that is robust, efficient, and repeatable across multiple views of the same scene. The simplest local feature is a point in an image that is distinct from its neighbors. Once identified, these points are labeled as interest points. Interest points can be caused by a number of local properties including lighting, texture, and structure. This work focuses on the interest points representative of local image structures such as corners and vertices. Junction points provide a more specific category

\* Tel.: +1 806 742 3527; fax: +1 806 742 3519. E-mail address: eric.sinzinger@ttu.edu. for these points with representatives including L, Y, T, and X junction points.

Each junction point contains a set of angular cuts that divides the neighboring region into non-overlapping wedges. The junction detection methodology presented in this paper introduces two new measures based upon radial interactions with putative junction points. The first measure relates an image gradient of an arbitrary point in the neighborhood of the putative point to the vector between the arbitrary point and the putative point. The second measure determines the spread of the points along an angular cut to determine if a strong angular value is caused by a few high impulses or a steady change along the entire length of the angular cut. These two measures are used to identify a set of potential angular cuts that divide the neighborhood about a point into wedges. An energy minimization algorithm is presented that examines subsets of the angular cuts to determine the minimal radial segmentation. Then a cascading

algorithm is used to identify the strongest junction points in local neighborhoods.

The next section presents a broad overview of corner detection with particular emphasis on signal-based and model-based approaches. The radial edge-based junction model presented in Section 3 describes the energy function used to represent the junctions. Section 4 provides an algorithm to apply a junction model to a point, minimize the energy, and determine if a point is a line or junction. The results are presented in Section 5 with tests performed on both synthetic images and real-world images. Conclusions are drawn and future work is proposed in the final section.

#### 2. Related work

There are three main categories of interest point detectors—curve-based, signal-based, and model-based. A review of interest point detectors current up to 2000 is provided in Ref. [1]. Curve-based methods use the edge points in a neighborhood. One type of curve-based method detects corners by tracing the edge points and responding to high levels of curvature [2–5]. The other main type of curve-based method groups edges to form lines, and then intersects the lines to determine the vertex position [6]. Both signal-based methods and model-based methods are closely aligned to the approach of the radial edge-based junction detector and are covered in more detail below.

Two primary criteria for evaluation of interest point detectors are localization accuracy [7] and repeatability [1]. Localization accuracy measures the deviation of the identified corner from the true center. Repeatability measures the detection of identical features in the same scene taken from different views. With the growing interest in wide baseline stereo [8], there has been an increased need for interest point detectors that are invariant to large deviations resulting from skew, rotation and other similar affine or homographic transforms. Comparisons and evaluation techniques of these methods can be found in Refs. [9,10].

### 2.1. Signal-based

One of the early interest point detectors was developed by Moravec for stereo vision control of an autonomous vehicle [11]. The goal of this interest operator is to identify a selection of points that are relatively uniform across the image. A measure of the variance of the image in four directions is used to select the points that have the maximum variance in a local neighborhood.

Kitchen and Rosenfeld [12] have provided a contrasting view to the prevalent contour-based techniques at the time of their work. Their signal-based operators search for extreme image gradient magnitudes and high image curvatures. Two of their main results are a discrete operator that approximates the curvature along image gradients and a continuous analog, which first performs a surface fit before computing curvature. To improve localization they recommend applying different size filters and point multiplying the results. To remove non-dominant corner points they use non-maximum suppression.

Due to its simplicity and speed, the Harris detector [13] is used often in practice. The image gradient is computed over the entire image. About each point, a small window is used to construct a correlation matrix between both components of the image gradient. The eigenvalues of the resulting  $2 \times 2$  matrix are calculated. If both eigenvalues are large, this means there are significant changes in two orthogonal directions, which implies a corner. Likewise, if one eigenvalue is dominant, then a corner is not identified.

The SUSAN corner detector [14] utilizes a count of pixels with similar intensities within the neighborhood of a given pixel. If the count is less than a given threshold, the pixel is classified as a corner. To remove false positives, the centroid and contiguity are examined. Finally, non-maximum suppression identifies the strongest corner candidate in a local region.

Ando [15] uses dimensionless operators derived from gradient covariances to identify likely regions for corners. Inside the likely regions, angular gradients are used to compute local changes. If an angular region has a much greater local change it is classified as a radial edge. If the number of radial edges is equal to or less than one, then the region is classified as a peak or dip. Otherwise, the region is classified as a corner, vertex or junction.

Mikolajczyk and Schmid [16] present a corner detector that identifies interest points along with an affine invariant neighborhood. A multiscale Harris corner detector is used to determine initial interest points. For each identified point, its second moment matrix across scale is used to determine the correct position, scale and space of the interest points. The method works well for interest points identified inside of flat planes with high information content. This technique has been further refined to be scale invariant [17].

Lowe developed the scale invariant feature transform (SIFT) to identify and represent local features [18,19]. SIFT identifies the extremum in the scale space, localizes the point and determines the orientation of the point. For the region, an affine covariant descriptor is constructed, even though the region may not be locally flat. Of additional note, the SIFT detector is a representation based upon a histogram of neighborhood orientations. This representation has been shown to be an effective discriminator for classification of noisy scenes [20].

#### 2.2. Model-based

Singh and Shneier [21] present both model-based and signal-based approaches. The model-based approach uses a specific template formed by a mask set at specified angles. Different measures are used to compute the deviation from the template. The signal-based approach fuses two gradient direction measures together through multiplication. The first gradient direction measure is based upon the Kitchen and Rosenfeld operator. The second gradient direction measure evaluates the change in gradient direction along an edge.

Blaszka and Deriche [22] present a model for multiple junctions that includes parameters describing the position, angles of the segments, the grey level intensities, and a blur factor. The

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