# Vessel Junction Detection From Retinal Images

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## Abstract

*This paper presents a perceptual organization based method for detecting Vessel Junctions (VJs) from retinal images. A retinal image is first segmented into edge traces which contain vessel boundaries. Each trace is divided into generic curve segments (GCSs) at curve partitioning points (CPPs). CPPs are the places on a trace from where the continuity of GCSs was broken according to perceptual organization criteria. The extracted CPPs and GCSs are the structure features of VJs. The detection algorithm uses CPPs as seeds for searching VJ patterns. VJs have two classes which include branching type and crossing type defined according to their structure features. Experiment results are provided.*

## 1 Introduction

Retina vessel extraction is very useful for medical diagnose applications [1,2,3,4]. A good vessel map will give us useful geometric information for the allocation of other objects in retina images, for instance lesions and so on. The changes of a vessel map can also closely relate to some disease symptoms such as diabetic retinopathy. There is a high demand for automatic or semi-automatic tools of detecting and measuring vessels or vessel-related data for efficient and accurate diagnose purpose.

People were seeking for good solutions in this field for more than ten years and have developed various methods in tackling the problems [4,5,7,8,9,10,11,12]. The main stream methods include matched filter [7,9,10], edge detecting and parallel tracking [4,12], etc. Although the matched filter method achieved some robustness in handling noise, but requires intensive computation. The edge detection based solutions seemed receiving more attentions because of the computation efficiency. However the most existing edge based methods [4,12] are mostly semi-automatic and require intensive input data from the human operator, such as the start and end points for detecting a vessel, parameters for parallel tracking, optic disc locations, etc. Vessel junctions are the control points for retina image registration [8,12], and often treated as start and end points for tracking individual vessels. It is hardly to see any publications which provide automatic junction detection and representation, rather the manual drawing methods were widely adopted.

In this paper we present an automatic method for detecting VJs. By applying an existing edge tracker, we convert an image into edge traces which cover vessel boundaries. Each trace is divided into Generic Curve Segments (GCSs) at Curve Partitioning Points (CPPs) based on perceptual organization principles [6]. The extracted CPPs and GCSs are then used as domain heuristics for detecting VJs. The preliminary results were showing that the proposed method has great potential for accurately locating VJs at a very low computation cost. Further, the method does not need the optic disc data in advance for locating VJs and therefore for tracking vessels.

In section 2, the perceptual organization model will be introduced. The details of junction representation and detection will be presented in section 3. Section 4 is experimental results and discussions. Conclusions and future research will be discussed in the last section.

## 2 Perceptual Organization Models of GCS and CPP

For qualitative curve shape recognition, Gibson suggested many years ago [13] that a simple visual line or border has two variable

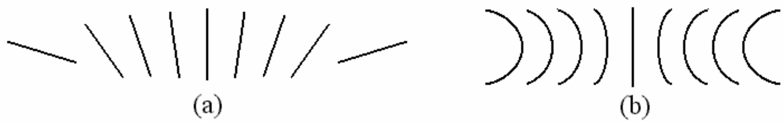



**Figure 1**: The qualities of a simple line observed by Gibson [13]: (a) "left slant…zero slant…right slant", and (b) "convex…straight…concave".

qualities besides length – one is "left slant .. zero slant .. right slant", and the other is "convex .. straight .. concave" as shown in Figure 1. A line looks as if it had those phenomenal properties and behaves in perception as if it had them. They may be referred as the quality of direction (linear slope) and curvature (linear shape). Mathematically, these two variables determine a curve at all of its points. Phenomenally, the two corresponding qualities determine a visual line or border in all of its segments. Gibson further suggested that if curvature and direction are variable qualities of a border, there is a possibility that a closed border – a form – may be reduced to variable qualities. These suggestions attempted to provide an explanation of how our retina carries out a fast transformation when objects moved around in a 3D world.

Although Gibson's observation and other psychological studies didn't provide direct explanations on possible approach or mechanism used by human vision in shape perception, they did conclude certain useful hints which may be useful in developing computation models for perceptual curve recognition. Gao [6] presented a qualitative model for curve recognition by partitioning and re-merging curves in terms of GCSs. The quality of a GCS can be defined based on certain perceptual organization rules (i.e., Gestalt laws), such as similarity, proximity, and continuity of the points lying on the GCS.

To derive qualitative shape descriptors, such as from Gibson's observations, we need to model the Gestalt laws for both GCS and CPP properly. The classification of GCSs should be based on the best breaking down curves in terms of the perceptual characteristics of GCSs. In the psychological experiments of curve partitioning [14], it is found that human subjects partition two-dimensional curves according to three different objectives. They tend to choose a set of contour points that: 1) best mark those locations at which distinctive curve segments are "glued" together; 2) best allow the reconstruction of the complete curves; 3) best allow a viewer to distinguish a given curve from the others. Figure 2 shows the examples of two partition methods, (a) the conventional method which breaks down curves based on the discontinuation of tangents and (b) the proposed method which partitions a curve based on the monotonicity discontinuation of descriptive characteristics including tangents (more detailed will be discussed shortly). The method (b) is chosen for curve partitioning because the partitioned segments are the most simple curve pieces and descriptively sound, which are corresponding to the GCSs given in Figure 3. Each GCS has its own unique descriptive characteristics and represents a general class of qualitatively distinguishable curve segments. The computation model of GCSs is introduced below.

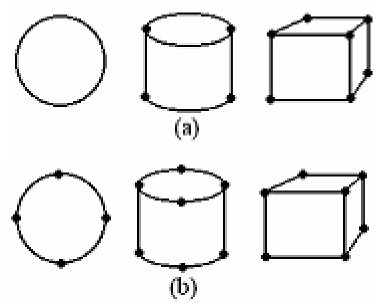



**Figure 2**: An illustration of two types of partitions: (a) Partitions based on discontinuation of tangents; (b) Partitions based on discontinuation of tangent monotonicity.

Analytic descriptors of polynomial curves have a general expression:

$$f(\boldsymbol{x}, \boldsymbol{a}) = 0 \qquad (1)$$

where $\boldsymbol{x}$ denotes an image point and $\boldsymbol{a}$ is a vector of parameters. The procedures of analytic solutions for detecting curves, as presented in many algorithms, are relying on calculating $\boldsymbol{a}$ for each edge pixel $\boldsymbol{x}$, such that $f(\boldsymbol{x}, \boldsymbol{a}) = 0$. In contrast, a generic curve segment GCS is expressed by

$$\text{GCS} = \{\boldsymbol{x} \mid p(\boldsymbol{x})\}, \qquad (2)$$

where $\boldsymbol{x}$ is an edge point, $p(\boldsymbol{x})$ indicates the point satisfies the property $p$, $\{\boldsymbol{x} \mid p(\boldsymbol{x})\}$ denotes a set of points sharing the property $p$, and GCS is a symbolic label of the set.

The property $p$ is the monotonic characteristics of GCS which can be qualitatively defined by a set of binary functions described in the following. Given a curve $y = f(x)$ and its inverse function $x = \varphi(y)$, their first derivatives are represented by $f'(x)$ and $\varphi'(y)$ respectively. The property $p$ of a point $\boldsymbol{x}$ can be fully described by the function set

$$p(\boldsymbol{x}) = \{ f(x), \varphi(y), f'(x), \varphi'(y)\} \qquad (3)$$

In other words, a GCS is a set of curve points which share a same property $p$. Figure 3 shows eight classes of GCSs which are qualitatively defined in Table 1.

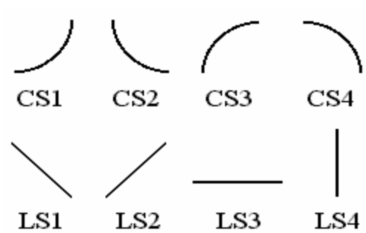



**Figure 3**: A set of generic curve segments (GCS).

| GCS | f(x) | φ(y) | f'(x) | φ'(y) |
|---|---|---|---|---|
| CS1 | M+ | M+ | M+ | M- |
| CS2 | M- | M- | M+ | M- |
| CS3 | M+ | M+ | M- | M+ |
| CS4 | M- | M- | M- | M+ |
| LS1 | M- | M- | c | c |
| LS2 | M+ | M+ | c | c |
| LS3 | c | N/A | 0 | ∞ |
| LS4 | N/A | c | ∞ | 0 |

**Table 1**. The definitions of CGS, where M+ and M- denotes monotonic increase and decrease respectively.

The GCSs are perceptual curve segments which can be used to group curves qualitatively. For instance, the classes CS1 to CS4 can be used to form various conic sections. The straight line segments LS1 and LS2 are defined according to two general groups of slopes: $0^o$ to $90^o$ and $90^o$ to $180^o$ respectively. LS3 and LS4 are special cases for horizontal and vertical lines. Accordingly, the points which break down curves into GCSs are the positions on the curves at which the transitions of monotonicity take place. These perceptually significant breaking points, i.e., CPPs, are the general types of joints of GCSs as illustrated in Figure 4 and Table 2. Although CPP1 to CPP4 are not view invariant, they are perceptually stable features and hence very useful for grouping curve structures.

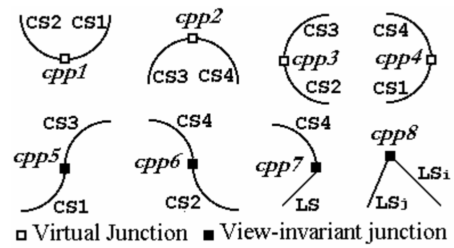



**Figure 4**: The definitions of CPPs.

| Rule # | Definitions |
|---|---|
| G1 | (CPP1, CS1, CS2) |
| G2 | (CPP2, CS2, CS3) |
| G3 | (CPP3, CS3, CS4) |
| G4 | (CPP4, CS4, CS1) |
| G5 | (CPP5, CS1, CS3) |
| G6 | (CPP6, CS2, CS4) |
| G7 | (CPP7, CS, LS) |
| G8 | (CPP8, LSi, LSj) |

**Table 2**. The definitions of CPPs (curve grouping rules).

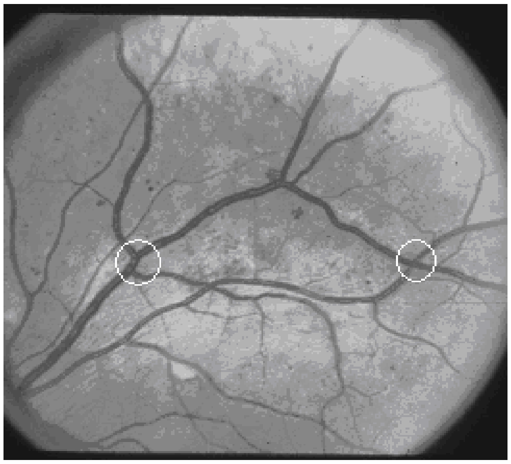
# 3 VJ Detection

## 3.1 VJ Structures

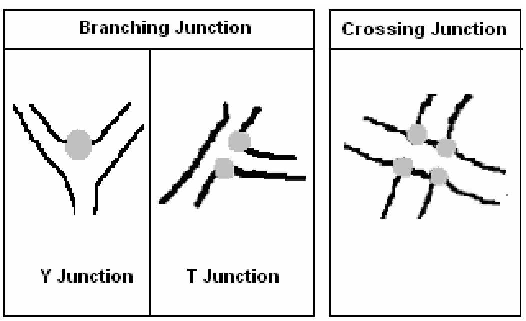
Vessel junctions may be divided into two general types as shown in Figure (5):

1) Branching or dividing junctions from where a vessel is divided into sub-vessels;
2) Crossing junctions from where two separated vessels are over crossing each other;

Branching junctions can be further divided into two subclass, i.e., Y junctions (we also call it bifurcation junctions) and T junctions as illustrated in Figure 5 (b). Y junctions correspond to the generic structure of one CPP and two associated parallel GCS pairs, and T junctions are defined by two CPPs and three associated parallel GCS pairs. In contrast, the type of crossing junctions has a generic structure of four CPPs and four associated parallel GCS pairs.



(a)




(b)

**Figure 5:** (a) Two types of junctions in circulated areas; (b) Two types of junction structures.

Associated parallel GCSs are two nearest GCSs which belong to the same perceptual class (see Figure 3, i.e. they have a same GCS label), and satisfy a pre-defined vessel width. We can detect them through the following procedures: 1) find all nearest GCS pairs from same GCS class, then 2) measure the distance for each associated pair. A pair of vessel GCSs is found if they passed the distance measure.

From Figure 5, one may compare the junction structures defined in (b) with the true vessel junctions observed in the original image (a), such as the two example cases marked by circles. In other words, CPPs are critical points which provide useful heuristics for grouping vessel junctions.

Curve partitioning focuses on the segmentation of generic curve features CPPs and GCSs according to the monotonic properties of GCSs which are perceptually significant edge primitives. Retina vessel boundaries are connected GCSs which are mostly smooth curve segments. The detection of vessel junctions is a process of grouping CPPs and associated parallel pairs of GCSs for matching the structure patterns defined in Figure 5 (b).

## 3.2 Edge Traces and Noise Removal

We applied an existing edge tracker for extracting edge traces (one pixel wide linked edge pixels). The result of edge trace map of the original image (Figure 5 (a)) is shown in Figure 6.

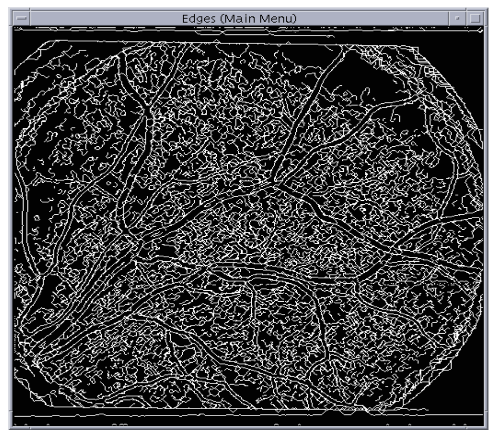
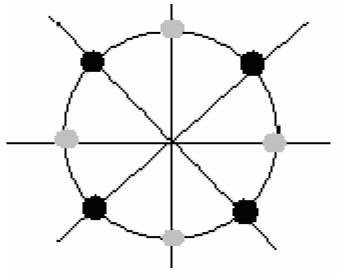



**Figure 6:** The detail edge traces extracted from the original image (Figure 5 (a)).

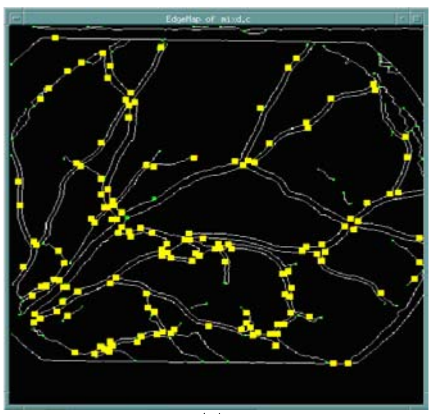
The edge tracker was implemented based on the perceptual model of generic curve segments presented in the previous section. Each vessel GCS can be segmented based on the following criteria: it has a) a continued edge strength (i.e. with low variance on edge uniformity), b) a minimum length, and c) a continued smoothness. The criteria provide strong constraints for suppressing the noises (i.e. non-vessel GCSs). Gaussian blurring is applied as a pre-processing for smoothing the edge map. Post processing is used to remove the short, non linear noise traces by tracking the first derivative along each edge traces.

## 3.3 VJ Detection Procedure

By tracking and monitoring the edge pixel's direction parameters, dx, dy (i.e. x and y gradients), and r (i.e. dy/dx), we can successfully allocate all the CPPs. Meanwhile, we also introduced a set of new CPP points which associated the direction changes at 45 degrees, as illustrated in Figure 7, for the purpose of enriching the sensitivity of GCSs direction changes for locating vessel junctions.



(a)



(b)

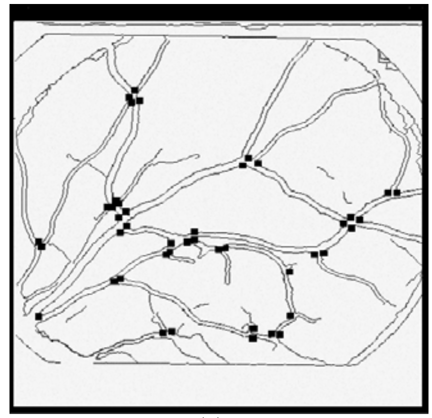
**Figure 7:** (a) New CPPs in black color and the old CPPs in grey color; (b) All CPPs including both new and old types.

A valid CPP is a junction seed which can be verified by finding its two associated parallel pairs of GCSs. Accordingly, the CPP map can be further reduced from Figure 7 (b) to Figure 8 (a).

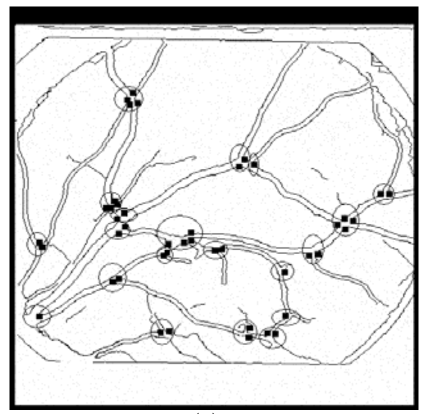
Through the tracking of the monotonic changes of edge traces, CPPs and GCSs are detected and classified. The extracted junction features are then used for searching and matching vessel junctions. The general procedure of junction detection is described below.

Vessel Junction Detection Procedure:

1) Extract edge traces from retina image:
   - Smooth image by Gaussian blurring
   - Apply the edge tracker to extract edge traces;



(a)



(b)

**Figure 8:** (a) Valid CPPs for grouping vessel junctions; (b) Grouped vessel junctions.

   - Remove short and non-linear noise traces;

2) Detect vessel junctions:
   - Tracking edge traces
   - Partitioning edge traces
     For each trace
     - Detecting CPPs
     - GCS classification
   - Vessel GCS segmentation by evaluating each GCS using the vessel GCS criteria
   - Vessel GCS grouping for associated parallel pairs
   - Vessel junction grouping
     - V junction grouping
     - T junction grouping
     - Cross junction grouping

Vessel diameters are ranging from 3-8 pixels for parallel GCSs matching. The grouping result of vessel junction detection was shown in Figure 8 (b), and marked with the circles.

The junction locations are defined by the centers of the junctions according to the notions described in Figure 9 to Figure 11.

Before we find the centers of the junctions, we need to know the branching pair points. Each junction can be described as several vessel segments intersecting in a spot. Before reaching the intersection spot, any points located on one of the two parallel boarders of a vessel segment can be matched to another parallel point located on it's pair vessel segment board through parallel tracking. The last pair points before reaching the junction spot are called branching pair points.

For crossing junction, we link the center point of two opposite branching pair points. The intersection of these two crossing line is defined as the location of this crossing junction (see the solid gray circle of the Crossing Junction picture shown below).

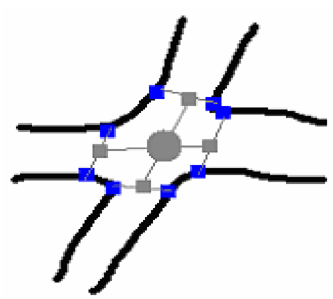


Figure 9: Locate center of Crossing Junction.

For Bifurcation Junction, we find the center point of two points located on same trace but belong to two different branching pair points. Then link all the three points to find the center point of this triangle. The center point as shown below in gray solid circle is defined as the location of Bifurcation Junction.

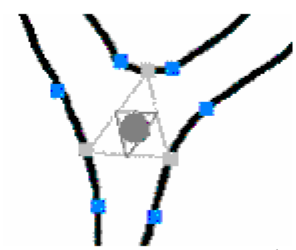


Figure 10: Locate center of Y (Bifurcation) Junction.

For T junction, we link the center points of two similar branches' (with similar branching direction) pair points, and then draw the second line from the center of the third branch's pair points towards the linked line along the reverse direction of that branch. The intersection is the location of T junction.

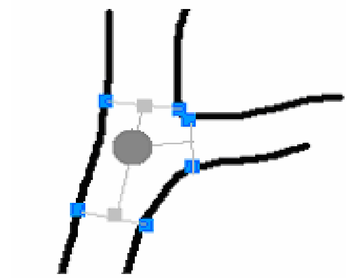


Figure 11: Locate center of T Junction.

### 3.4 Result Discussion

Testing result of the junction detection is shown in Figure 8. The sensitivity of the detection on the specified two kinds of junctions is extremely high on our testing image. Curve partitioning method provides an efficient way in handling junction detection.

Though the testing result shows a very high sensitivity of junction detection, the detection algorithm still need to be further improved to accommodate varies kinds of retina images. The junction detection algorithm assumes we should be able to detect all the junction CPP points. However, some junction CPPs' locations may not be correctly detected because of the noise objects near the CPP or rotation of the junction structure.

## 4 Conclusion

This paper presented a preliminary result of applying perceptual organization models for vessel junction detection from retina images. The perceptual models of curve partitioning and grouping were succeed in providing a set of generic edge tokens. The segmented edge tokens are examined and grouped into vessel segments and junctions. Since the token features are descriptive in nature, therefore they can be handled qualitatively in promoting robustness and efficiency. In further research, we will conduct more experiments on various cases. Meanwhile we will investigate how to combine more domain heuristics of retina images into the perceptual edge tracking mechanism for improving the current implementation.

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