

Utilizing Road Network Data for Automatic Identification of Road Intersections from High Resolution Color Orthoimagery

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Abstract

Recent growth of the geo-spatial information on the web has made it possible to easily access various and high quality geo-spatial datasets, such as road networks and high resolution imagery. Although there exist efficient methods to locate road intersections from road networks for route planning, there are few research activities on detecting road intersections from orthoimagery. Detected road intersections on imagery can be utilized for conflation, city-planning and other GIS-related applications. In this paper, we describe an approach to automatically and accurately identifying road intersections from high resolution color orthoimagery. We exploit image metadata as well as the color of imagery to classify the image pixels as on-road/off-road. Using these chromatically classified image pixels as input, we locate intersections on the images by utilizing the knowledge inferred from the road network. Experimental results show that the proposed method can automatically identify the road intersections with 76.3% precision and 61.5% recall in the imagery for a partial area of St. Louis, MO.

1. Introduction

Recent advances in remote sensing technology are making it possible to capture geospatial orthoimagery (i.e., imagery that created so that it has the geometric properties of a map) with a resolution of 0.3 meter or better. These

images are available online and have been utilized to enhance real estate listings, military targeting applications, and other GIS applications. One of the key issues with these applications is to automatically identify man-made spatial features, such as buildings, roads and road intersections in raster imagery. Computer vision researchers have long been trying to identify features in the imagery [1]. While the computer vision research has produced algorithms to identify the features in the imagery, the accuracy and run time of those algorithms are not suited for these real-time applications.

Integrating existing vector data, such as road network data, as part of the spatial feature recognition scheme alleviates these problems. For example, the spatial information of road network data represents the existing knowledge about the approximate location of the roads and intersection on imagery. In addition, the attribution information of road network data, such as road names and address ranges, can be utilized to locate and annotate buildings on imagery [2]. However, accurately and automatically integrating geo-spatial datasets is a difficult task, since there are often certain spatial inconsistencies between geo-spatial datasets. There are multiple reasons why different data products may not align: they may have been collected at different resolutions, they may use different spheroids, datums, projections or coordinate systems, they may have been collected in different ways or collected with different precision or accuracy, etc. Conflation is often a term used to describe the integration or alignment of different geospatial data sets.

The conflation [3] process can be divided into following subtasks: (1) Feature matching: Find a set of conjugate point pairs, termed control point pairs, in two datasets, (2) Match checking: Detect inaccurate control point pairs from the set of control point pairs for quality control, and (3) Alignment: Use the accurate control points to align the rest of the points and lines in both datasets using the triangulation [4] and rubber-sheeting

<i>Publisher</i>	<i>PubDate</i>	<i>OrdinateRes</i>	<i>WestCoord</i>	<i>EastCoord</i>	<i>NorthCoord</i>	<i>SouthCoord</i>
USGS	2003	0.3	-90.63578	-90.61862	38.38338	38.36987
USGS	2003	0.3	-90.63534	-90.61818	38.39689	38.38338
USGS	2003	0.3	-90.63490	-90.61773	38.41039	38.39689
:	:	:	:	:	:	:

(a) Sample (partial) metadata of USGS high resolution color orthoimagery

<i>Source</i>	<i>AreaCovered</i>	<i>Projection</i>	<i>Pub-Date</i>	<i>CFCC classification</i>	<i>WestCoord</i>	<i>EastCoord</i>	<i>NorthCoord</i>
USGS 1:100k DLG	El Segundo, CA	Lambert Conformal Conic	1998	Secondary roads	-90.44	-90.423	38.582
USGS 1:100k DLG	St. Louis, MO	Lambert Conformal Conic	1998	Primary roads	-118.4351	-118.3702	33.9164
USGS 1:100k DLG	St. Louis, MO	Lambert Conformal Conic	1998	City streets	-118.4351	-118.3702	33.9164
:	:	:	:	:	:	:	:

(b) Sample (partial) metadata of U.S. Census Bureau TIGER/Lines

Table 1: Sample metadata of orthoimagery and road networks

techniques. One major difficulty with current conflation techniques is that they require the manual intervention often including identification of a set of control points for feature matching to properly conflate two data sets.

Various GIS researchers and computer vision researchers have shown that the intersection points on the road networks provide an accurate set of control point pairs [5, 6, 10]. One cannot rely on a manual approach to locate road intersections to perform conflation, as the area of interest may be anywhere in the world and manually finding and filtering road intersections for a large region, such as, the continental United States, is very time consuming and error-prone. Moreover, performing conflation offline on two geo-spatial datasets is also not a viable option in online applications as both datasets may be obtained by querying different information sources at run-time. Therefore, an automatic approach to identifying road intersections in diverse geo-spatial datasets, especially in orthoimagery, is needed. Moreover, road intersections can not only be used for geo-spatial data fusion, but can also be utilized for transportation-related GIS [7], city-planning and GIS data updating, etc.

In this paper, we propose an approach to automatically identify and annotate road intersections on high resolution color imagery. In particular, we utilize road network data and imagery metadata to both improve the accuracy and reduce the running time of image analysis techniques. Consequently, the entire road detection process can be done without any manual intervention in real time. Experimental results show that our proposed method can automatically identify the road intersections with 76.3% precision and 61.5% recall in the imagery for a partial

area of the county of St. Louis, MO. To the best of our knowledge, automatically exploiting these auxiliary structured data to improve the image recognition techniques has not been studied before.

The remainder of this paper is organized as follows. Section 2 describes our overall approach. Section 3 illustrates the techniques to label image pixels based on imagery metadata and Bayes classifier. Section 4 presents an image processing technique utilizing knowledge inferred from road network data to detect road intersections on imagery. Section 5 provides experimental results. Section 6 discusses the related work and Section 7 concludes the paper by discussing our future plans.

2. Overview

Recently, metadata (i.e., information about data) is used increasingly in geographic information systems to improve both availability and the quality of the spatial information delivered. Table 1 shows sample metadata about USGS high resolution color orthoimagery¹ and the road network U.S. Census Bureau TIGER/lines². We exploit metadata from both imagery and road network data to perform the automatic road intersection detection procedure.

For the imagery, we can exploit the ground resolution and geo-coordinates to measure real world distance between any two spatial objects or perform image

¹ <http://seamless.usgs.gov>

² <http://tiger.census.gov/cgi-bin/mapsurfer>

processing techniques (such as edge-detection, region-segmentation and histogram-based classification) at the pixel level to extract primitive entities, such as corners, edges and homogeneous regions, etc. For vector data of roads, we can exploit metadata about the vectors, such as address ranges, road names, or even the number of lanes and type of road surface. In addition, we can analyze the road network to determine the location of intersections, the road orientations and road shapes around the intersections. This inferred knowledge from road network data can then be augmented with information retrieved from imagery. For instance, we can find the approximate location of intersections on the images from the metadata of vector data, while the information (such as edges or pixel intensity) on imagery can be utilized to locate the exact location of intersections nearby the approximate locations. In sum, these automatically exploited information are dynamically exchanged and matched across these geospatial datasets to accurately identify road intersections.

Figure 1 shows our overall approach. Using chromatically classified image pixels as input, we locate intersections on the images by utilizing the image metadata and the information inferred from vector, such as approximate location of intersections, road-directions, road-widths, and road-shapes. In addition, identified intersections could be annotated with the vector information, such as road names and zip code.

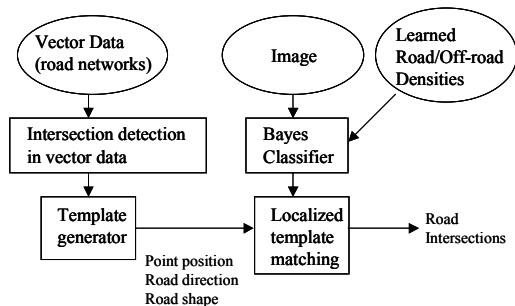


Figure 1: Overall approach

3. Labeling imagery using Bayes classifier

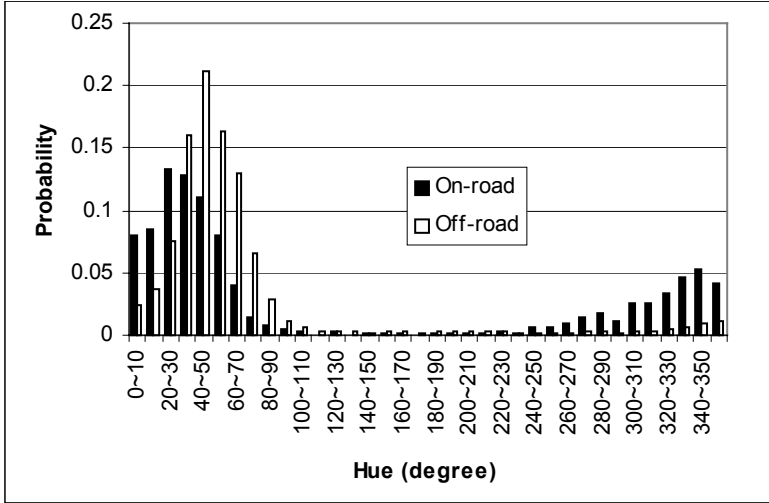
Towards the objective of identifying road intersections, the first vital step is to understand the characteristics of roads on imagery. On high resolution imagery, roads are exposed as elongated homogeneous regions with almost constant width and similar color along a road. In addition, roads contain quite well defined geometrical properties. For example, the road direction changes tend to be smooth, and the connectivity of roads follow some topological regularities. Road intersection can be viewed as the intersection of multiple road axes and it is located at the overlapping area of these elongated road regions. These elongated road regions form a particular shape around the intersection. Therefore, we can match this

shape against a template derived from road network data (discussed next) to locate the intersection. Based on the characteristics of roads, the formation of this shape is either from detected road-edges or homogeneous regions. However, on high resolution imagery, more detailed outlines of spatial objects, such as edges of cars and buildings, are considered as noisy edges. This makes perceptual-grouping based method used for road-edges linking a difficult task.

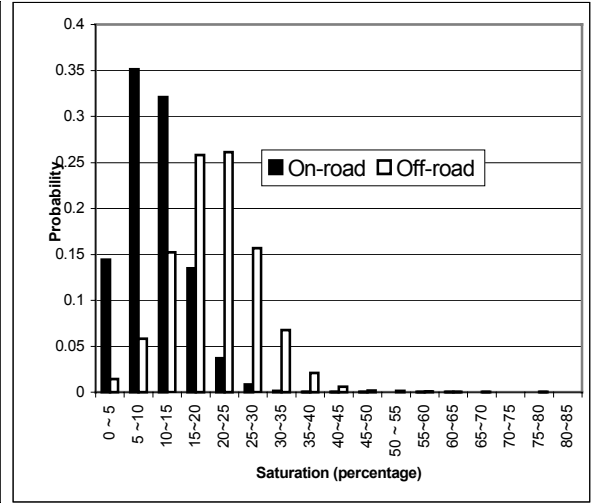
In contrary to edge-detection, we propose a more effective way to identify intersection point on color imagery by using Bayes classifier, a histogram based classifier [8, 9], to classify images' pixels around road network data as on-road or off-road pixels. The classification is based on the assumption of consistency of image color on road pixels. That is, road pixels can be dark, or white, or have color spectrum in a specific range, but still we expect to find the same representative color on close by road pixels. We construct the statistical color distribution (called class-conditional density) of on-road/off-road pixels by utilizing histogram learning technique as follows. We first randomly select a small partial area from the imagery where we intend to identify road intersections. Then, we interactively specify on-road regions and off-road regions respectively. From these large amount of manually labeled training pixels, we learn the color distribution (histograms) for on-road and off-road pixels. Hence, we can construct the on-road and off-road densities.

Figure 2 shows the hue probability density and saturation probability density³, after conducting the learning procedure on nearly 50,000 manually picked pixels of 2% of a set of USGS 30cm/pixel imagery (covering St. Louis County in Missouri of the United States). To illustrate, consider the hue density function on Figure2(a). It shows the conditional probabilities $Prob(Hue/On-road)$ and $Prob(Hue/Off-road)$, respectively. The X-axis of this figure depicts the hue value grouped every 10 degrees. The Y-axis shows the probability of on-road (and off-road) pixels that are within the hue range represented by X-axis. For a particular image pixel, we can compute its hue value h . Given the hue value h , if the probability for off-road is higher than on-road, our system would predict that the pixel is an off-road pixel. As shown in Figure 2, these density functions depict the different distribution of on-road and off-road image pixels on hue and saturation dimensions, respectively. Hence, we may use either of them to classify the image pixels as on-road or off-road. In our experiments, we utilized hue density function for

³ Due to lack of space, we eliminated the intensity (i.e., brightness of HSV model) density function. In fact, there is no obvious difference between the brightness distribution of on-road and off-road pixels, since these images were taken at the same time (i.e., under similar illumination conditions).



(a) Hue density function



(b) Saturation density function

Figure 2: Learned density function on HSV color space for On-road/Off-road pixels

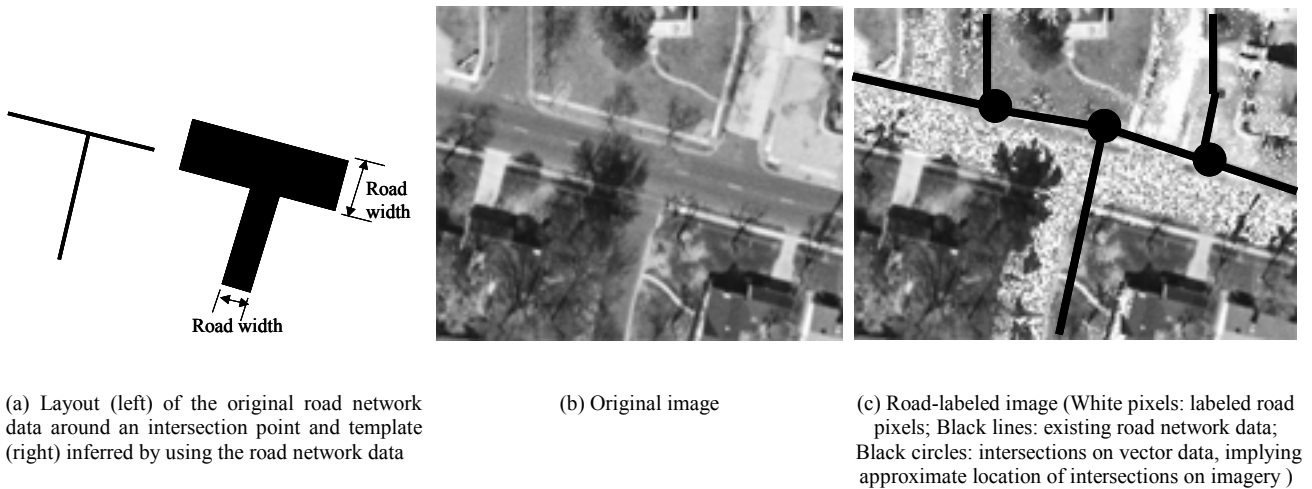


Figure 3: An example of the localized template matching

classification. In general, we can utilize the two chromatic components, hue and saturation, together.

Based on the learned hue density functions, an automated road-labeling is conducted as follows. A particular image pixel whose hue value is h is classified as road if

$$\frac{p(h/road)}{p(h/non-road)} \geq \theta, \text{ where } \theta \text{ is a threshold. } \theta$$

depends on the application-specific costs of classification errors and it can be selected using ROC technique discussed in [9].

Since we know the approximate intersection locations on the images from the road network data (discussed next), the road-labeling procedure is applied only to image pixels within a radius of potential intersections.

Therefore, we do not need to exhaustively label each pixel on the entire image.

4. Analyzing imagery using road network data

Using the classified image (an example is shown in Figure 3(b)(c)) as input, we can now match it with a template inferred from the road network data to identify intersections. We term this procedure as localized template matching (LTM). First, our LTM technique finds the geo-coordinates of all the intersection points on the road network data. Since we also know the geo-coordinates of the images (from image metadata), we can obtain the approximate location of intersections on the imagery (as in Figure 3(c)). For each intersection point on

the road network data, LTM determines the area in the image where the corresponding intersection point should be located. The area size can be determined based on the accuracy and resolution (such as ground resolution from image metadata) of the two datasets. One option is conducting experiments using various sizes and selecting the size that has better performance (discussed in Section 5).

For each intersection point detected from the road network data, LTM picks a rectangular area in the image centered at the location of the intersection point from the road network data. Meanwhile, as an example shown in Figure 3(a), a template around an intersection on road network data is generated by the presence of regions inferred from the road network data using information, such as the road directions and road widths. LTM will then locate regions in the road-labeled image (see Figure 3(c)) that are similar to the generated template (as in Figure 3(a)) as follows. Given a template T with $w \times h$ pixels and road-labeled image I with $W \times H$ pixels, we move the template around each pixel at the image and compare the template against the overlapped image regions. Our adapted similarity measure is a normalized cross correlation defined as:

$$C(x, y) = \frac{\sum_{y'=0}^{h-1} \sum_{x'=0}^{w-1} T(x', y') I(x+x', y+y')}{\sqrt{\sum_{y'=0}^{h-1} \sum_{x'=0}^{w-1} T(x', y')^2 \sum_{y'=0}^{h-1} \sum_{x'=0}^{w-1} I(x+x', y+y')^2}}$$

where $T(x, y)$ equals one, if (x, y) belongs to a road region, otherwise; $T(x, y)$ equals zero. $I(x, y)$ equals one, if (x, y) is pre-classified as a road pixel, otherwise; $I(x, y)$ equals zero. $C(x, y)$ is the correlation on the pixel (x, y) .

The highest computed correlation $C(x, y)$ implies the location of the best match between the road-labeled image and template. In addition, an intersection will be identified, if $C(x, y)$ is greater than a threshold t ($0 < t <= 1.0$). We set the threshold t to 0.5. Hence, the best-matched point will be characterized as an intersection only if it is at least quasi-similar to the vector template.

The histogram-based classifier as illustrated in previous section may generate fragmented results, due to some noisy objects, such as cars, tree-clusters and building shadings on the roads. Furthermore, some non-road objects whose color is similar to road pixels might be misclassified as roads. However, LTM can alleviate these problems by avoiding exhaustive search of all the intersection points on the entire image and often locates the intersection point on the image that is the closest intersection point to the intersection point detected from the road network data. Moreover, this technique does not require a classifier to label every pixel for the entire region. Only the areas near the intersections on the image need to be pre-classified.

Figure 4 shows an image indicating the intersection points on road network data and the corresponding intersection points identified on imagery. One of the accurately identified intersections is annotated with the road network information, such as road names and zip code.

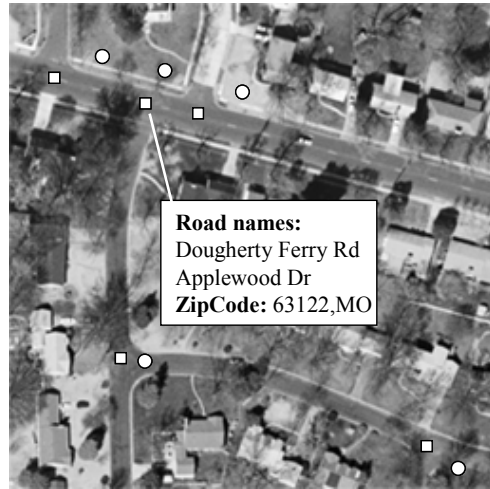


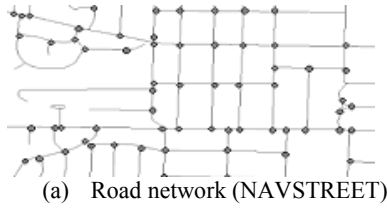
Figure 4: The intersections (circles) on road network data and the corresponding intersections (rectangles) on imagery.

5. Performance Evaluation

We conducted several experiments to evaluate our approach by measuring the precision and recall of the identified road intersections against real road intersections. For our experiments, we used a set of 0.3m/pixel resolution color orthoimagery (covering St. Louis County in Missouri of the United States) from USGS and road network data from NAVTEQ⁴ and U.S. Census TIGER/Lines. In general, both road network data have rich attribution but TIGER/Lines has poor positional accuracy and poor road shapes. We learned the histogram (as shown in Figure 2) from nearly 50,000 manually picked pixels of 2% of these images. Then, we applied our approach to identify intersection points on randomly selected areas of these images (about 9% of this imagery). There are about 1200 intersections in total on these tested areas. Figure 5 shows 8% of the NAVTEQ road network data and 0.48% of the image area used in our experiments. The off-line learning process requires manual intervention to obtain conditional density functions, but it is performed only when new imagery dataset is introduced to the system. In addition, we can apply the learned results to automatically identify intersections of the area that is much larger than the area we learn from.

We applied a “buffer method” to evaluate recall and precision. When multiple elongated road regions merge at

⁴ <http://www.navteq.com/>



(a) Road network (NAVSTREET)
 (b) USGS Orthoimagery
Figure 5: A partial area of tested data

an intersection, their overlapping area at the intersection is a polygon (called buffer). Identified road intersections that fall within the buffer are considered as “accurately identified intersections”. Using this term, we define:

$$\text{Recall} = \frac{\text{Number of accurately identified intersections}}{\text{Number of intersections in the image}}$$

$$\text{Precision} = \frac{\text{Number of accurately identified intersections}}{\text{Number of identified intersections}}$$

For each type of road network data, the area radius, a fixed constant used in LTM, was determined by conducting experiments using various sizes. An experimental result for NAVTEQ data (on an area with 106 intersections) is shown in Figure 6. In Figure 6, we also demonstrate the normalized intersection detection running time (with respect to the running time of using 180m as radius) to show that the detection time

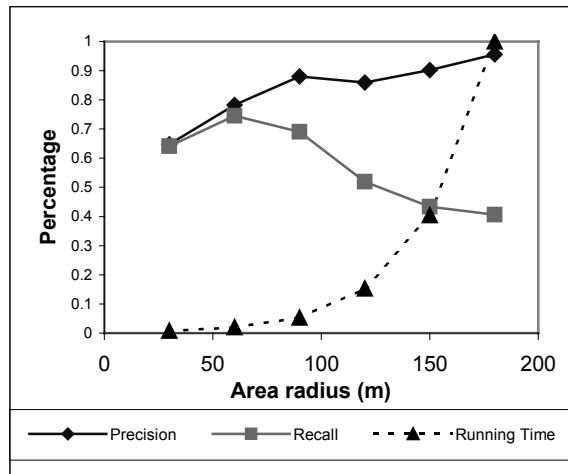


Figure 6: The impact of area radius (Radius is increased by 30 meters, i.e. 100 pixels on imagery)

dramatically increases as area size increases. We selected 90m as our area radius for the rest of experiments. When setting the radius to 90m, we achieved 88% precision. Although it is less than the precision obtained using 180m as radius, we have much better recall (70% v.s. 40%) and 20 times better running time.

For the overall tested area, on the average, we obtained 76.3% precision and 61.5% recall with NAVTEQ data and 62% precision and 39.5% recall with TIGER/Lines. If we exclude the intersections detected on highways where the road widths vary and difficult to predict, we achieved 83% precision and 65% recall with NAVTEQ data. In order to explain our experiments, we show the performance of a sub-area (with 106 intersections) of the larger tested area in Table 2. As shown in Table 2(a), there are originally more than 30 intersection points on the NAVTEQ vector that match with the corresponding intersections on images, while there are only about four of these intersections on the TIGER/Lines. This is because the NAVTEQ vector data has a very high accuracy. Nevertheless, we significantly improved the precision and recall of both vector data.

	Precision	Recall
Original NAVTEQ	31.2%	31.5%
Localized Template Matching (LTM)	88%	69%
LTM with VMF filter	98%	53%

(a) Identified Intersections using NAVTEQ road network

	Precision	Recall
Original TIGER/Lines	4.1%	3.5%
Localized Template Matching (LTM)	71%	41%
LTM with VMF filter	91%	27.4%

(b) Identified Intersection Points using TIGER/Lines

Table 2: Road Intersection Identification Evaluation

Now, suppose we want to use our detected intersections as control points for a matching problem, such as the vector to imagery conflation problem described in Section 1. The conflation process does not require a large number of control point pairs to perform accurate alignment. In fact, a smaller set of control points with higher accuracy would serve better for the conflation process [10]. Therefore, for the conflation process higher precision is more important than higher recall. Towards this end, we can use a filter to eliminate misidentified intersections and only keep the accurately identified intersections, hence improving the precision with the cost of reducing the recall. VMF [10] is an example of such filter. As shown in Table 2, the VMF filter improves the precision, although it reduces the recall.

The VMF filter works based on the fact that there is a significant amount of regularity in terms of the relative positions of the intersections on the vector and the detected (corresponding) intersections on the imagery across data sets. More precisely, first the geographic coordinate displacement between the intersections on the road network and detected (corresponding) imagery intersections is modeled as 2D vectors. Next, for a small

area, the vectors whose directions and magnitudes are significantly different from the median vector are characterized as inaccurate vectors. By eliminating these vectors, we can filter out their corresponding misidentified intersections. Before applying VMF, there are three misidentified intersections (marked as 1, 2 and 3) of 21 intersections in Figure 7(a). The displacement between these 21 road network intersections and detected (corresponding) imagery intersections is shown with the arrows (Figure 7(b)). The thickest arrow is the vector median among these displacement vectors. After applying VMF, the eleven (half of the identified intersections) closest vectors to the vector median were kept. As shown in Figure 7(c), the three misidentified intersections are filtered out.

6. Related work

Automatic identification of road intersections is a complex procedure that utilizes work from a wide range of subjects, such as knowledge discovery from metadata of vector and raster data, spatial (geometric) pattern recognition and digital image processing.

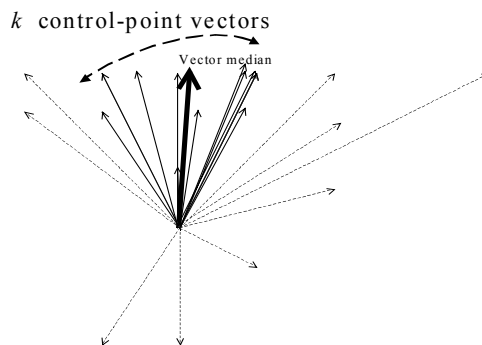
Many studies have been focussed on road or man-made object extractions from images [5, 11]. In particular, an on-road/off-road histogram is learned for black-white images in [12], while we deal with color images. Flavie et al. proposed techniques in [5] to find the junctions of all detected lines on images, then matched the extremities of the road vector with detected image junctions. Their method suffers from the high computation cost of finding all possible junctions. Road intersections are salient and useful features, particularly in solving matching problems, such as conflation [10, 13], GIS data correction [14] and imagery registration [15]. Most of the research activities in spatial data and GIS are centered around issues such as data representation, storage, indexing and retrieval. However, recent growth of the geospatial information on the web has made geospatial data conflation one of central issues in GIS [16]. In addition to efficiently storing and retrieving diverse spatial data, the users of these geospatial data products often want these different data sources displayed in some integrated fashion. Figure 8 shows the conflation results utilizing LTM detected intersections as control points and the conflation techniques proposed in [10]. Moreover, the intersections detected on images can match with the intersections detected on maps [6, 17] for the measure of the similarity of different spatial scenes. In addition, road intersections have been utilized for many transportation-related systems such as [7]. To the best of our knowledge, automatically exploiting these auxiliary structured data to improve the image recognition techniques has not been studied before.

7. Conclusion and future work

In this paper, we focus on the two commonly used spatial data storage and display structures: vector and raster.



(a). The intersection points (rectangles) on vector data and the corresponding intersection points (circles) on imagery.



(b). The distributions of twenty-one displacement vectors



(c). The intersections left after applying vector median filter on Figure 7(a).

Figure 7: VMF filter



Figure 8: Vector-Imagery conflation (White lines: original road network; Black lines: after applying conflation using identified intersections)

There have been a number of efforts to efficiently determine all intersection points from large number of line segments [18] of vector data (e.g., road networks), while there is little work on efficiently and accurately identifying road intersections from raster data (e.g., satellite imagery). The main contribution of this paper is the design and implementation of a novel approach to automatically identify and annotate road intersections on high resolution color orthoimagery. Our approach utilizes Bayes classifier, road network data and image metadata to detect road intersections. Although our histogram-based classifier requires extra operations to learn the conditional density functions, we can apply the learned results to automatically identify intersections of the area that is much larger than the area we learn from. Moreover, our approach is the first that exploits the metadata of imagery and vector data to take full advantage of all the available information from both datasets to achieve the automatic road intersection detection. We have also demonstrated the utility of our approach through several empirical experiments.

The accurately identified and annotated intersections can not only be utilized for geo-spatial data fusion, but can also be used for transportation, city planning and spatial data mining, etc. For example, the identified intersections on image are annotated with vector attributes, such as road names, road directions and zip codes. We can then build an approximate zip code map on the image, using these intersections and the technique proposed in [19]. In future, we plan to utilize the similar techniques to identify road intersections on maps.

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