Automatic Alignment of Vector Data and Orthoimagery for The National Map

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ABSTRACT
A general problem in combining road vector data with orthoimagery from different sources is that they rarely align. There are a variety of causes to this problem, but the most common one is that the latest products are collected with higher accuracy and improved processing techniques. In previous work, we developed techniques to automatically correct the alignment of vector data with orthoimagery using a technique called conflation. However, in applying our technique to real-world datasets provided by USGS, we discovered that these techniques failed in some areas. In this paper, we describe some refinements to our original approach that provide consistently better results in aligning the vector data with the orthoimagery.

Categories and Subject Descriptors
I.4 [**Image Processing**]: Feature Measurement; I.2 [**Artificial Intelligence**]: Learning

General Terms
Algorithms

Keywords
orthoimagery, vector data, conflation, alignment

1. INTRODUCTION
The National Map is a government effort to make geospatial data available for the US beginning with the 133 urban areas of the Homeland Security Infrastructure Program (HSIP). The purpose of this project is to make these integrated datasets available to government organizations to support science, crisis response and emergency planning, among other applications. Currently, the U.S. Geological Survey (USGS) is collecting high resolution 0.3 meter orthoimages under contracts to industry. Vector data including transportation, hydrography, boundaries, and structure outlines, from a variety of sources including federal, state, local and tribal governments, must be aligned with the orthoimages (Figure 1). The problem is that there are no automated techniques for aligning vector data with orthoimagery and this is a very labor intensive task.

Figure 1: Poor Alignment of Roads with Orthoimagery Before Processing

Under our NSF-funded ITR grant, we developed an approach to automatically align road vector data with high resolution orthoimagery. This approach exploits the road vector data to perform a highly focused search for the corresponding intersection points in the orthoimagery. The result is a set of accurately identified intersections that can serve as control points to align the vector data with orthoimagery. While these techniques provide significantly better alignment of the vector data with the orthoimagery in most places, there are, however, some regions where the alignment of the vector data is worse than the original.

2. PREVIOUS WORK
In previous work, we developed techniques for automatic conflation of road vector data with orthoimagery. The most effective technique we found exploits a combination of the knowledge of the road network with image processing in a technique that we call *localized template matching* [2]. With this approach, we first train the system on a small area of the orthoimagery to learn the road color distribution based on the image pixels' hue value. We then classify image pixels as road/non-road regions by applying a Bayes classifier with this hue distribution. Meanwhile, the system locates road intersection points from the road vector dataset. For

Figure 2: Further Degraded Alignment Caused by the Failure to Locate the Intersections

Figure 3: Accurate Alignment of Roads with Orthoimagery After Algorithm Improvements

each intersection point, a template inferred from the vector information (e.g., road width and directions) is matched against the localized area around the intersection to find the corresponding intersection in the pre-classified image. By exploiting the road direction and width information we improve both the accuracy and efficiency of detecting intersections in the image.

An issue that arises is that the localized image processing may still identify incorrect intersection points, which introduces noise into the set of control point pairs. It is essential to use a filter to eliminate misidentified intersections and only keep the accurately identified intersections, hence improving the precision at the cost of reducing recall. We use the Vector Median Filter (VMF), which 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 corresponding intersections on the orthoimagery across data sets. More precisely, VMF first interprets the coordinate displacement between the intersections on the vector and corresponding orthoimagery intersections as 2D vectors (termed as control-point vectors). Next, a given intersection is kept as a control point if it is within k% (k is a predefined constant) of the vectors that are closer to the median vector.

3. IMPROVING THE ALIGNMENT

With the test sets described in [2], the approach described above produced an accurate alignment of the vector data with the orthoimagery. However, in applying our technique to real-world datasets provided by USGS, we discovered these techniques failed in some areas (Figure 2). Two major issues cause this failure: first, some image pixels are misclassified mainly because only one color channel (i.e., hue) is utilized to categorize the road/non-road regions. Second, we set a very high threshold for filtering control points, which provided high precision, but low recall on the control point pairs. We improved the accuracy of the vector-imagery alignment by developing techniques to address these issues.

To improve the road classification, we switched to a machine learning classifier, called a Support Vector Machine (SVM), to categorize image pixels based on all available image color information (i.e., RGB). An SVM maps all training data into a high-dimensional Hilbert space and then generates region boundaries as hyperplanes separating data points. We utilized the freely available SVM library SVMLIB [1] as the learning method to learn the road color (RGB) distribution to predict image pixels as road/non-road pixels.

To address the low recall due to the VMF filtering technique, we developed a cluster-based approach to dynamically choose the filtering threshold, k, for diverse regions. In VMF, we used vector median whose summed distance to other neighboring control-point vectors is minimal to filter outliers. The similar vectors tend to form clusters around the median vectors. Based on this observation, we modified the filtering technique to accommodate more vectors that are close to the median vector. More precisely, instead of filtering based on a fixed percentage, we changed the system to dynamically choose different k for diverse areas based on two types of distributions of the control-point vectors: (1) if the vectors form a cluster around the median vector, the system keeps the control-point vectors in the cluster, and (2) if there is no obvious cluster for the control-point vectors, the system will set k to 70%.

4. DISCUSSION

Experimental results show that the new classification technique and improved filtering provides significant improvement on precision and recall for identifying intersections. This in turn results in improved vector-imagery conflation results (Figure 3). The remaining challenge is to improve the accuracy of the intersection detection in areas around highways. Highways pose a particular challenge because of their varying widths. Once we have addressed this issue, we will run a comprehensive evaluation of the techniques in several different regions covered by *The National Map.*

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6. REFERENCES

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