AUTOMATED EXTRACTION OF TRAFFIC INFORMATION FROM SATELLITE IMAGERY

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ABSTRACT

The increased availability of high resolution remote sensing imagery has opened up for new opportunities for road traffic monitoring applications. Vehicle detection from satellite images has a potential ability to cover large geographical areas and can provide valuable additional information to traditional ground based equipment. This is especially the case for remote rural roads where ground based counting can be both expensive and difficult. In this paper we present a solution for satellite-based traffic counts intended for such roads. The solution, which is currently under development, aims at covering all steps necessary in the process of extracting this information, and several novel approaches have been developed to achieve this.

***Index Terms*—** traffic information, road segmentation, cloud detection, vehicle detection, contextual analysis.

1. INTRODUCTION

Traffic statistics is a key parameter for operation and development of road networks. The primary source of traffic statistics today is ground based counts generated from various types of equipment mounted in or close to the road. Important statistics describing traffic are derived from these counts. The most important one is the so-called AADT (Annual Average Daily Traffic), which is the average number of vehicles passing a location during one day, taken as an average over a year. In Norway AADT is estimated using ground based vehicle counts in combination with statistical models. However, for fairly large parts of the Norwegian road network AADT is still unknown. This is especially the case for roads in rural districts where installation and operation of equipment for ground based counts are both difficult and expensive.

Over the last few years, very high resolution satellite sensors have opened up for alternative means of obtaining traffic statistics. A significant advantage of satellite based technology is that it does not require installation of equipment in the road, and one image can cover a large geographical area. In this paper we present a solution for satellite-based traffic counts on remote roads intended to cover all the necessary steps in the process of estimating the counts necessary for AADT computations.

There are a few existing approaches addressing the problem of extracting traffic information from satellite images [6][7][10], but most of these studies focus on larger roads like highways, and none of these describe solutions for the full process needed to achieve an operational system. The solution presented in this paper aims at addressing all the necessary steps, including road segmentation, cloud detection and vehicle detection. To handle this, a set of novel information extraction approaches have been developed, aimed at enabling robust performance under varying conditions as needed for an operational solution.

2. METHODS

In our approach automatic road segmentation is performed by using a novel approach for combining GIS data and an image to obtain a suitable representation of the region of interest where an active contour model is applied in the search for the road. Areas occluded by clouds or lying in the cloud shadows are identified through land cover classification based on spectral features, where a specialized approach has been developed to cater for variations in conditions (atmospheric, botanic and phenological) between training and test images. Vehicles are detected through a two-stage approach, where a novel elliptical blob detection algorithm in scale space is applied to identify vehicle candidates, and contextual analysis is used to separate vehicle candidates from tree shadows. Finally, spectral, geometric and contextual features are extracted and used to classify the candidates as vehicles or non-vehicles, obtaining the traffic counts. Through the next sections these methods are described in some more detail.

2.1. Automatic road segmentation

The detection of vehicles from satellite images requires that the road to be analyzed has been identified and masked out in the image. Vector data are available from a GIS and need to be exploited both to identify the right roads, as there may be several roads covered by an image, and to find the position of the road in the image. If the images and vector data were very accurately co-registered, the road could be delimited simply by selecting an area corresponding to the width of the road around the vector data. Unfortunately, this is seldom the case.

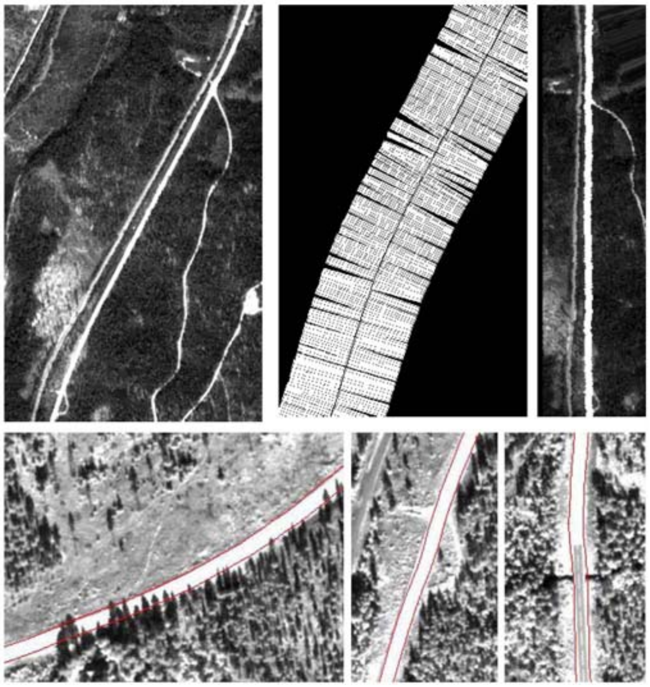

Figure 1:Top: Transformation to alternative representation. Bottom: Results from segmentation.

Although the vector data and image data are not accurately co-registered, the vector data will still provide useful information about the approximate position and trace of the road. We therefore use this information to extract an area in the image around the road vector with a size relative to the expected magnitude of the geographical displacement. We extract such an area by sampling the image along lines perpendicular to the road vectors, where the result of this transformation is a long and narrow image along the road (Figure 1, top). In the case where the vector and image data are perfectly co-registered, the road will run as a straight line along the middle of this image. But still, when this is not the case, the complexity of the road trace will be greatly reduced through this transformation. Hence, we can limit both the search area and the search direction simplifying the problem of finding the road in the image.

In this new representation we know that the road should run through all the lines of the transformed image. Hence, we should be able to find and trace the road by analyzing this image line by line. To do this we use a *snake-based* approach. Snake models initialized by road vector data have also previously been used for road extraction [1], however our transformed image space greatly simplifies the process. We determine the external and the internal forces, where the external force is found from the transformed image data and designed to find the road, which typically appears as a bright ribbon, by computing the average over a window corresponding to the expected width of the road. The internal force is based on local smoothness of the trace of the road, where the assumption is that the position on two adjacent lines will not change dramatically. We then use dynamic programming (Viterbi) to find the set of points that optimize the sum of internal and external forces over the whole set of lines.

As the road surface in the panchromatic image will appear as rather heterogeneous, the road segmentation approach is performed in the multispectral resolution where the blue band was found to be the best choice. The resulting road mask is then resampled and adjusted through to achieve a smooth panchromatic representation.

2.2. Automatic cloud and cloud shadow detection

In order to increase the performance of the system, images that are partly covered by clouds will also need to be included in the analysis. However, when using cloud contaminated images cloud and cloud shadow masks are required both to estimate the correct observed road length for the statistics, and to assist the vehicle detection algorithm. To detect clouds and cloud shadows in the images we apply a classification based approach. A main challenge here is that there may be a poor match between training data and test data due to atmospheric, geographic, botanic, and phenological variations of the image data. To solve this we build on earlier approaches [4][11] that aim at exploiting intrinsic relationships between the training and test data to adapt the training data distributions to the distributions describing the classes in the test domain

Training data for each class is constructed by visual inspection and labeling of regions in a set of training images with reduced resolution. Our set of classes included clouds, cloud shadows, green vegetation, water, haze and bare ground (concrete, asphalt, soil etc.). We model the data representing each class using a multivariate Gaussian distribution where the mean vector and covariance matrix is estimated from the training data.

Although the data distribution for a given class varies between the training images, and also varies between the training images and the test images, the training data domain and test data domain are generally neither identical nor uncorrelated. This makes it possible to utilize the existence of an intrinsic relationship between the two data domains, and adapt the training data distributions to the distributions describing the classes in the test domain [11].

Bruzzone and Prieto [4] proposed a method for retraining a classifier when test data differs (slightly) from the acquired training data. Although appealing, it suffers from a weakness in the sense that many parameters need to be estimated. When applying this method to our data we obtain a very good statistical fit of the likelihood to the test image, but the mixture components have no longer a physical meaning in the sense that, e.g. the mixture component of a given land cover type no longer models that land cover type, but something else. Building on this method we have therefore developed an alternative approach which applies a low rank modelling of the parameters in order to

Figure 2: Clouds (red outline) and cloud shadows (blue outline) have been identified.

reduce the number of degrees of freedom and the flexibility of the model. By doing so, we force the class structure of the training data to be maintained in the test image. We also extend the method by incorporating several training images, each with different class dependent data distributions.

For cloud detection we model each class of a given training and test image using band 2 and 3 as features with Gaussian distribution. We assume that the covariance matrix of a given class in the test image is simply the average covariance matrix of all training images, and the corresponding mean vector is the average mean vector of all training images plus a component of rank one. For cloud shadow detection we have also included NDVI and the ratio between band 2 and 4 as features. We model a given class mean vector in the test image as a weighted average of the corresponding training image mean vectors (constrained to have only non-negative weights). The classification process is a two-stage procedure, where we in the first stage classify the clouds, and in the second stage classify the cloud shadows. The detected cloud pixels are masked out in the test images prior to the cloud shadow classification stage.

As a postprocessing step an additional contextual analysis is performed where information about the azimuth and elevation angle of the satellite and the sun is used to remove falsely detected shadow areas. The shadow of each cloud is located in the opposite direction relative to the sun apparent azimuth. Since there is no need to resolve the clouds with high resolution, we perform the described cloud classification on an image down-sampled by a factor of 8.

2.3. Vehicle detection

The vehicle detection uses a two-stage approach of object segmentation followed by classification of these objects as vehicles or non-vehicles (first introduced by Eikvil et al [5]). The segmentation stage is based on scale space elliptical blob detection and aims at finding image objects representing possible vehicle candidates. Since vehicles have an elliptical shape in high resolution satellite images, we have extended the scale space circular blob detection approach proposed by Blostein and Ahuja [3] to the more general approach of detecting elliptical blobs. The image is convolved with an elliptical Laplacian of Gaussian filter at various scales. Locations where the estimated scale is close to the scale of the filter, and the estimated contrast is higher than a preset threshold, are treated as points of interest. Details on the scale space filtering step can be found in [9].

After having identified these points of interest, we extract the vehicle silhouettes from the list of candidate vehicle centers, i.e., we define the spatial extension of the blob surrounding the blob center. The object silhouettes are found using a simple region growing technique starting from the blob center. Once we have found the object silhouettes, we can extract many features describing the objects, and use classification to separate vehicles from non-vehicles.

For dark vehicles there is a risk that these are grown together with tree shadows along the road. Hence a special algorithm is used to separate dark vehicles from tree shadows [9]. This algorithm is based on the observation that while vehicles may have grey levels similar to the tree shadows, the shape of the region can still reveal that there is a vehicle connected to the tree shadow. Based on the characteristics of the contour of the region around the transition zone from vehicle to shadow, two criteria of the presence of a vehicle have been defined: (i) the border contour of the region has a strong negative curvature, and (ii) the outward normal vector of the contour points of the region is in the same direction as the road. These two criteria form the basis of our algorithm for separating dark vehicles from tree shadows. In addition, contextual information based on sun angle and a vegetation mask derived from the multispectral image, are used to identify areas along the road where tree shadows may appear.

The objects remaining as potential vehicle candidates are classified using a hierarchical scheme. First objects are classified as either dark or bright according to the appearance relative to the background. Then these two classes are classified separately. The features used in this classification are based on spectral, geometric, and contextual characteristics, and slightly different feature sets are used for the dark and the bright objects. Classification is performed using a K-nearest-neighbor classifier with K = 3, classifying the objects as either vehicle or non-vehicle.

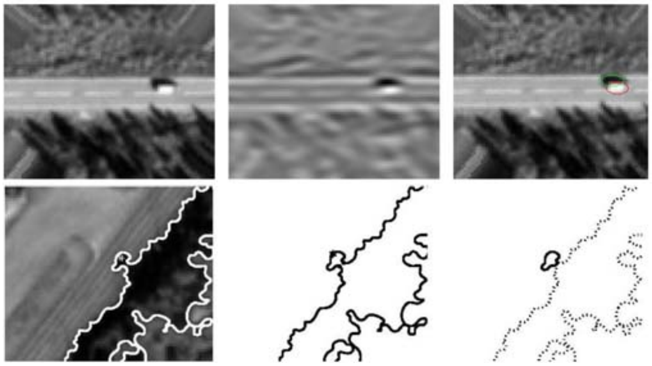

Figure 3:Top: Elliptical blob detection. Bottom: Separation of vehicle objects from tree shadows.

3. RESULTS

3.1. Road segmentation

The road segmentation approach was applied to a set of Quickbird and WordView-2 scenes covering approximately 120 kilometers of road. Visual inspection showed a smooth road mask and demonstrated that the algorithm was robust with respect to the existence of trees and tree shadows occluding parts of the road, and was also able to handle road surfaces with changing spectral response. The algorithm can however be confused by bright objects/areas appearing very close to the road. Still, this is less of a problem for rural areas which is the designated application area for our solution. For use in urban areas an extension of the algorithm to the use of the full multispectral information could reduce the problem.

3.2. Cloud and cloud shadow detection

The algorithm was applied to a large set of Quickbird and WorldView-2 scenes, covering many different areas in Norway. The approach was evaluated through visual inspection and showed good performance. In addition to being able to detect clouds and cloud shadows, the approach was also able to distinguish clouds from haze. However, as the current algorithm is intended for summer images some snow covered areas were misclassified as clouds. Still, including a winter image may have some undesirable effects since the spectral signature of snow is similar to clouds.

3.3. Vehicle detection

The algorithm has been evaluated on a set of 6 Quickbird panchromatic satellite images with 0.6m resolution covering approximately 70 kilometers of road and containing 182 vehicles. The results show that we are able to detect vehicles that are fully connected with the cast shadow, and at the same time ignore false detections from tree shadows. The performance evaluation shows that we are able to obtain a detection rate as high as 94.5%, and a false alarm rate as low as 6%.

4. CONCLUSIONS

A first approach covering the main steps needed for a fully automatic satellite based system for extraction of traffic information has been developed. The different steps have been tested on a variation of scenes, covering long stretches of rural roads, and show promising results. Future work will focus on full integration of these steps to reach a fully operational solution. To achieve this, the algorithms' performance will need to be adapted to each other, and problems related to robust handling of potential errors and inaccuracies will need to be handled.

Initial research on the expected quality of AADT using today's statistical model [2], given the availability of one or a few satellite images per year has also been performed. For roads with relatively large AADT as seen in a national context the results were promising, with the precondition that the vehicle detection algorithm is fairly accurate. Hence, the currently achieved detection rates of 94.5% demonstrate that a satellite-based solution is a viable alternative for obtaining traffic statistics.

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