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Automatic Traffic Data Collection Using Simulated Satellite Imagery

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인공위성영상을 이용한 교통량측정 자동화

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Abstract

The fact that the demands on traffic data collection are imposed by economic and safety considerations raises the question of the potential for complementing existing traffic data collection programs with satellite data. Evaluating and monitoring traffic characteristics is becoming increasingly important as worsening congestion, declining economic situations, and increasing environmental sensitivities are forcing the government and municipalities to make better use of existing roadway capacities. The present system of using automatic counters at selected points on highways works well from a temporal point of view (i.e., during a specific period of time at one location). However, the present system does not cover the spatial aspects of the entire road system (i.e., for every location during specific periods of time); the counters are employed only at points and only on selected highways. This lack of spatial coverage is due, in part, to the cost of the automatic counter systems (fixed procurement and maintenance costs) and of the personnel required to deploy them. The current procedure is believed to work fairly well in the aggregate mode, at the macro level. However, at micro level, the numbers are more suspect. In addition, the statistics only work when assuming a certain homogeneity among characteristics of highways in the same class, an assumption that is impossible to test when little or no data is gathered on many of the highways for a given class.

In this paper, a remote sensing system as complement of the existing system is considered and

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implemented. Since satellite imagery with high resolution is not available, digitized panchromatic imagery acquired from an aircraft platform is utilized for initial test of the feasibility and performance capability of remote sensing data. Different levels of imagery resolutions are evaluated in an attempt to determine what vehicle types could be classified and counted against a background of pavement types, which might be expected in panchromatic satellite imagery. The results of a systematic study with three different levels of resolutions (1m, 2m and 4m) show that the panchromatic reflectances of vehicles and pavements would be distributed so similarly that it would be difficult to classify systematically and analytically remotely sensing vehicles on pavement within panchromatic range. Analysis of the aerial photographs show that the shadows of the vehicles could be a cue for vehicle detection.

요 약

최근 안정성과 경제성을 고려한 교통자료획득 방법으로 인공위성 영상자료를 사용하는 기술이 논의되어졌다. 본 논문은 인공위성영상을 이용한 고속도로 교통량 측정 자동화에 관한 연구로서, 현재 사용되고 있는 교통량 측정방법의 단점 및 문제점을 평가, 분석하였으며, 본 보고서에서 제안된 인공위성영상을 이용한 방안의 적용 및 가능성을 연구, 분석 하였다.

기존 인공위성 영상자료의 해상도가 교통자료획득에 적합하지 않으므로, 사진영상에 제안된 방안을 도입하여, 실효성에 바탕을 둔 적용 여부를 검증하였다. 차량종류 및 교통량 측정에 필요한 인공위성영상의 해상도를 구하기 위하여 세 단계 (1m, 2m, 3m)의 사진영상해상도가 검토되었으며, 본 연구에서 제안된 일련의 영상처리 결과를 분석하였다.

전색성(panchromatic) 영상에서 도로와 차량의 반사율이 유사함으로, 도로상에서 차량을 탐지하기 위하여 차량의 반사율을 이용하지않고 차량그림자의 반사율을 이용하였으며, 두가지 처리방법이 제시되었다. 또한 차량종류를 구분하기위하여 여러가지 형태계수를 개발, 적용하였으며, 처리과정을 상세히 설명하였다.

1. Introduction

Quantifying the efficiency and effectiveness of existing traffic systems and facilities is essential and requires continual estimation and measurement of traffic characteristics. The principal parameters that require measurement and data collection are volumes, speeds, densities, and compositions, along with the resultant measures of flow efficiency and safety of travel times and headways. Evaluating and monitoring traffic characteristics is becoming increasingly important as worsening congestion, declining economic situations, and increasing environmental sensitivities are forcing the government and municipalities to make better use of existing roadway capacities.

There is no doubt that a large shift has occurred from adding more roadways and facilities to one of maximizing the use of existing facilities with improved and more comprehensive management techniques. Likewise, the upgrading and maintenance of existing infrastructure are growing concerns, since much of the infrastructure is nearing, or even past, time for repair and replacement. In recent time, government and municipalities began to conduct before and after project measurements of traffic volumes, speeds, concentrations and compositions at finer spatial levels than currently required.

The present system of using automatic counters at selected points on highways works well from a temporal point of view (i.e., during a specific period of time at one location). However, the present system does not cover the spatial aspects of the entire road system (i.e., for every location during specific periods of time); the counters are employed only at points and only on selected highways. This lack of spatial coverage is due, in part, to the cost of the automatic counter systems (fixed procurement and maintenance costs) and of the personnel required to deploy them. The current procedure is believed to work fairly well in the aggregate mode, at the macro level. However, at micro level, the numbers are more suspect. In addition, the statistics only work when assuming a certain homogeneity among characteristics of highways in the same class, an assumption that is impossible to test when little or no data is gathered on many of the highways for a given class.

Given these observations, it is clear that a remote sensing system providing improved spatial coverage and resolution would complement the existing system. Synoptic coverage provided by a satellite would be worth exploring, since it would allow more coverage of a region and provide improved estimates at more disaggregate levels. If a satellite could provide repetitive coverage for a wide swath area, while counters are providing temporal data on vehicle movement, the spatial coverage of the existing system might be greatly improved. For example, satellite "snapshots" at specific times could tie traffic characteristics on segments with no automatic counters to those segments with counters to estimate spatial variability among roads. If this spatial variability were assumed constant in time, the satellite data could be used to extrapolate traffic characteristics from the segments with continuous ground counts to those without such counts during periods when there is no satellite coverage. Satellite views could also be used to test whether sampled roadways (i.e., roads and locations along these roads where data are gathered using mechanical counters) are representative of the roads in the class; if they are not, the categories could be refined. Satellite measurements are also safer, since fewer personnel would be required to interfere with vehicle traffic to install and operate ground measurements. These "snapshots" could also be used identify troublespots for either temporary or permanent deployment of traffic counters.

Since satellite imagery with high resolution is not available, digitized panchromatic imagery acquired from an aircraft platform is utilized for initial test of the feasibility and performance capability of remote sensing data. Different levels of imagery resolution are evaluated in an attempt to determine what vehicle types could be classified and counted against a background of pavement types, which might be expected in panchromatic satellite imagery.

2. Traffic Data Collection

Traffic data is currently gathered via traffic engineering studies that obtain empirical facts about existing roadway conditions and vehicular traffic movements. Such studies involve obtaining data by measurements in the field. The recording or observation can be done manually or with some sort of "automatic" collection technology. The automatic technology may be either electronic or mechanical and may be set up either as a permanent or portable installation. These field measurements then add to existing databases at the government and local levels.

2.1. Manual Collection of Data

At locations such as intersections, where turning movements, approach volumes and queues are required, volumes are collected manually. Observers tally and write down the required data. When volumes are to be recorded for short periods (on the order of a few hours), manual collection is frequently preferred. Normally, the short duration does not justify the installation of automatic recording equipment.

Manually collecting data represents a problem with accuracy of recording when writing on field sheets or entering data into laptop computers, due to human error. The principal disadvantage of manually recording data is the amount of people required and the associated expenses in personnel time to cover a large number of locations. However, manual counts do offer some advantages. Manual collection allows information on travel directions and turning movements at intersections. It also can provide classification of vehicles by type, size and occupancy. Also, queue lengths and delays can be observed and recorded.

2.2. Automatic Vehicle Recording

Mechanical or automatic recording devices are used when data are to be collected over extended periods of time longer than a few hours, usually for collecting data for 24 hours or longer. One method is to use a road tube on the road surface across the width of the roadway. The tube utilizes the pneumatic pulse of air created when vehicle wheels pass over it, closing an electric circuit. The count records the number of axles. Since not all vehicles have just two axles, multi-axle vehicles produce an overcount that must be accounted for by correction factors. If vehicles arrive simultaneously in adjacent lanes, an undercount may also be produced.

Moreover, road tubes can be damaged by the impact of vehicle wheels and other physical damage. They also do not function when a vehicle is stopped with its wheels on the tube and not usable on gravel roads due to possible damages.

Other portable counters may be actuated by tape switches, which consist of wires taped to the roadway surface. When a vehicle crosses the wire, it closes a low current circuit or disturbs an electromagnetic field, which in turn actuates the detector. The tape switches can also be damaged, since they are on the surface of the road.

Underpavement detectors are loop or magnetic detectors. Loop detectors are commonly used on high volume, multi-lane roads, since loop detectors can distinguish vehicles in separate lanes. Magnetic detectors consist of a wire coil embedded in the roadway surface. The detector measures the difference in the level of the Earths magnetic forces caused by the presence of a vehicle. There have been many other detectors developed; pressure sensitive detector, sonic detector, and optical and video cameras.

2.3. Potential of Remote Sensing Techniques

There are generally two types of remote sensing systems - passive and active systems. Passive sensors record reflected and emitted energy from an object, whereas active sensors provide their own energy source and records the reflected signal from the object. Most remote sensing imagery used today is in a digital format. This allows for easy incorporation into a digital data base, such as a geographic information system (GIS). Electromagnetic radiation is recorded by photon detectors in electro-optical sensors. These detectors are sensitive to predefined wavelengths. Normally data is recorded in 8 bits or 256 shades of gray that correspond to reflectance levels on the ground.

Present commercial satellite systems such as U.S. Landsat and SPOT are sun-synchronous and polar-orbiting with coverage limited to the morning hours. Moreover, the spatial resolutions of these commercial satellite systems are too coarse to measure vehicle counts and speeds. Satellite technology should be at a stage to attain higher-resolution data capabilities within the next five years. For example, four commercial companies have been awarded licenses by U.S. Department of Commerce to market high-resolution satellite data. Those companies have 1-meter or 3-meter panchromatic imagery systems.

An objective of this research is to define the sensor requirements necessary for distinguishing vehicle types from a satellite platform *in the future*, given what we know from an aircraft platform *today*. Most traffic monitoring tasks being done today involve monitoring the traffic flow on a continuous basis. This is done using high resolution video cameras. However, in this study we are evaluating the potential of using satellite images acquired at various instants of time to provide an image that would be integrated with point measurements of the traffic conditions.

3. Vehicle Detection and Identification Using Simulated Satellite Imagery

McCord et al. [1995] reported that the vehicle reflectances and pavement reflectances resulting from the scanned representations of the aerial photographs were so similar that they were not able to detect and identify vehicles on the road. The author realized that their efforts required a subjective evaluation and selection of the proper threshold, and wanted to obtain better accuracies of vehicle identification and classification through advanced image processing techniques.

This image processing technique would also make the procedures more automated and objective in scope. Also, many more highway segments could be analyzed using this consistent approach. The author considered three major components in the development: image processing for edge detection and noise removal, representing the shape of the edges by several parameters, and developing constraints or heuristic rules designed for vehicle detection.

3.1 Vehicle Detection

A sequence of image processing tasks was developed to process a simulated satellite image into a final image showing candidate cars (see Figure 1). As mentioned, it is difficult to classify vehicles on the pavement using their reflectances. Thus, in this study, the shadows cast by the vehicles on the road are utilized for detecting and identifying vehicles.

To start the process, the original image is filtered using either a low pass filter (smoothing) or a median filter. The purpose of this step is to remove any noise in the image, but still preserve existing edges. Smoothing filters for noise reduction in the images were investigated. It was found that the median filter provided the best noise reduction, while still preserving the edges in the original image.

Next, using information from a transportation network file that may be contained in a GIS, the roadway network is registered with the satellite image. Knowledge of the spatial coordinates of the road location can be used to overlay on the satellite image. Two parallel lines, which are on either side of the highway, are developed knowing the width of a given type of highway. These lines defining the road network are then overlaid on the image file and the highway network is extracted from the image. The resulting image shows the extracted road network. The roads with vehicles can be from either a filtered image or the original satellite image, depending on the quality of the satellite image data. After then, a buffer on either side of the road centerline can be

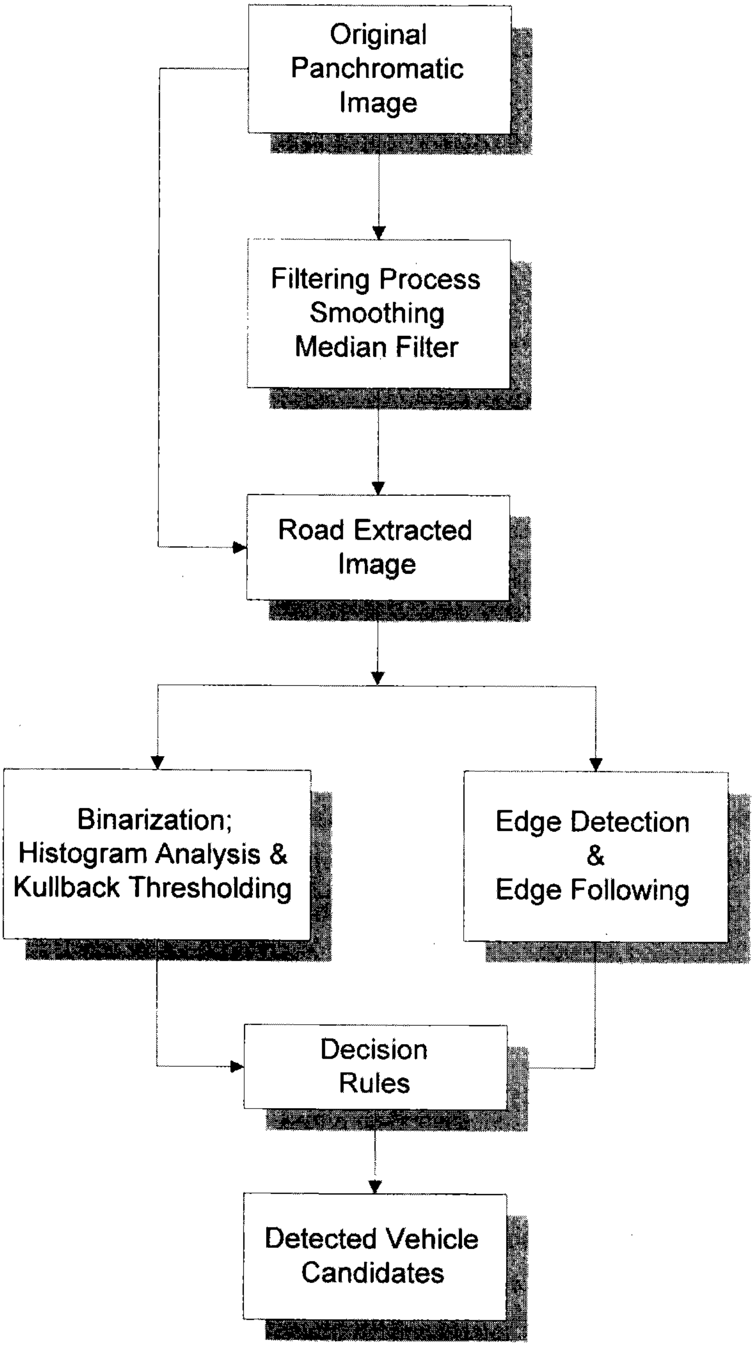


Figure 1. Image Processing Flowchart for Detecting Vehicles

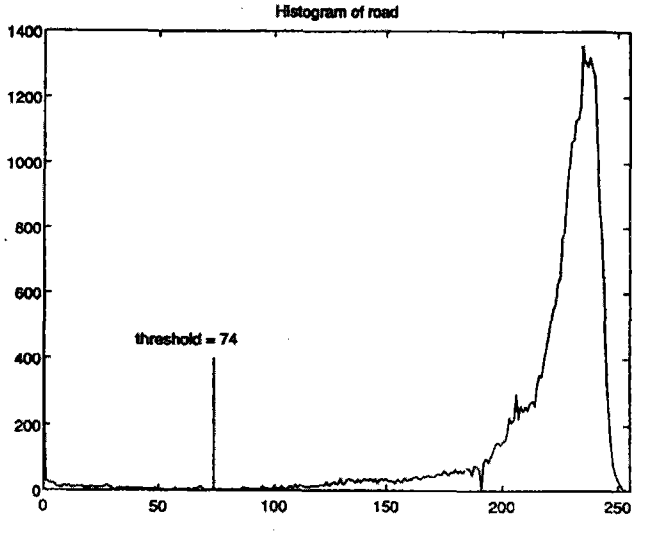


Figure 2. An example of histogram analysis and Kullback thresholding

created to eliminate the clumps representing the median strip.

The road-extracted image is then processed in two ways to produce information on the existence of vehicles on the extracted road segment. The first process uses only the gray scale values contained in the image-binarization process. Selection of the threshold value to separate the vehicles from the background pavement is critical. The histogram analysis and Kullback thresholding process is used to extract two histograms from an image gray level distribution. The assumption for this is that there are two distributions of gray tones - the pavement and the vehicle shadows. Thus, the two histograms correlate to the pavement pixels and the vehicle shadows, with the distributions assumed to be Gaussian. The technique used is a modification of the Kittler and Illingworth method. The main thrust of this technique is to minimize the Kullback information distance because we have a set of observations from a mixture of two Gaussian distributions (the pavement and the vehicle shadows). This modification will provide an automatic threshold of the image. The program then calculates the gray scale value that shows the optimum dividing line between the two distributions. Figure 2 show an example of automatic threshold value. Again, this is a global process to assist in analyzing the distribution of gray scale values of the image to identify potential vehicle candidates.

On the right-side of Figure 1, concurrent with the process on the left-side, the original (or filtered) image is subjected to an edge operator. This process results in an edge strength image that shows the strength of the mapped edges. Thus, the stronger the edge, the more likely it is to be associated with a vehicle. The edges are then connected with the edge following algorithm to result in an image of detected vehicle candidates. The edge strength provides local information that the binarization process cannot produce.

Several edge operators were used: Kirsch, Prewitt, Laplacian, LoG and Navatia operators. We found that the Laplacian and LoG operators did not detect the edges as well as the Kirsch, Prewitt and Navatia operators. In applying a step edge operator, such as the Prewitt or Kirsch, the key factor is to decide on a threshold value. To aid in this process, a histogram of scores (or strengths) of the edges defined by the edge operator is generated and analyzed on a global level for the image. A number of edge images can be generated for different threshold numbers. Based on an analysis of the histogram, a threshold number that corresponds to 3-4% of the edge scores is selected. However, if we find that the edges detected by the selected threshold number is not enough to generate edges, then the program automatically reduces the threshold number to generate more edges at the local level.

3.2. Vehicle Identification

The vehicle detection process results in images showing clumps (or boundaries) that correspond to vehicle shadow locations. Decision rules were developed to identify and classify potential vehicle "clumps" into vehicle types. A flowchart of these decision rules and the input parameters necessary for calculation are shown in Figure 3. The decision rules include the vehicle's shadow area, shadow perimeter, shadow area and perimeter ratio, shadow major axis length, shadow major axis and minor axis ratio, and shadow orientation. These parameters are calculated to sort the vehicle clumps into various classes. The area and perimeter values are used to correct (or discard) any long strips of median pavement that may have been misclassified into the vehicle list.

4. Experiments and Results

The image processing technique was applied to seven highway segments in the aerial photographs at three simulated resolutions (1, 2, and 4m) resulting from the scan rates. All segments were on interstate routes (I-70 and I-270) in the west-central or central part of Franklin County, Ohio (see Figure 4).

The aerial photographs were scanned using Optronics 5040 scanner at the OSU's Center for Mapping. The original scanned images then were resampled to 2 and 4 meter resolution images by using Gaussian kernel. Figure 5 shows the Highway 513 segments at three different resolutions.

Based on the panchromatic images, the use of filtering does not make a significant

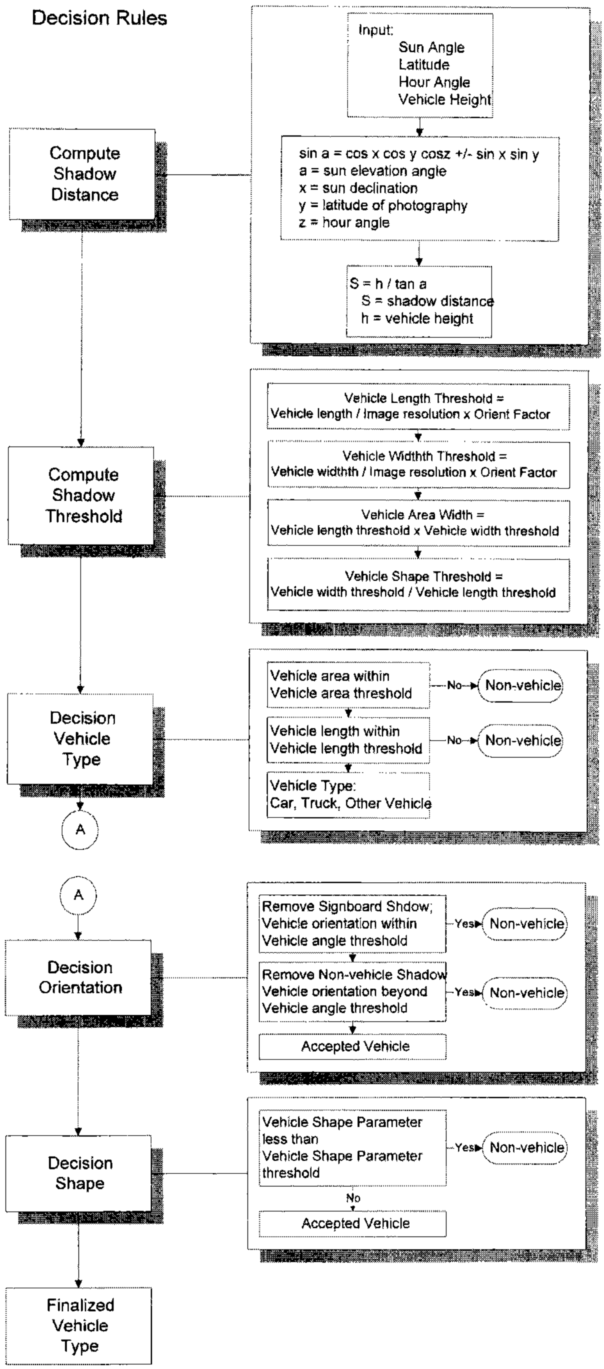
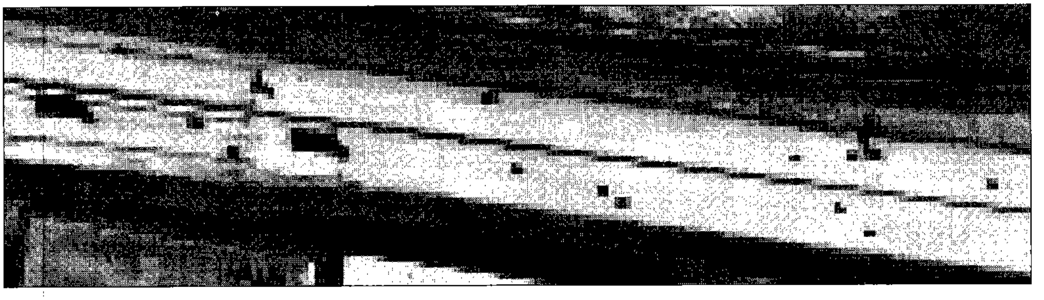


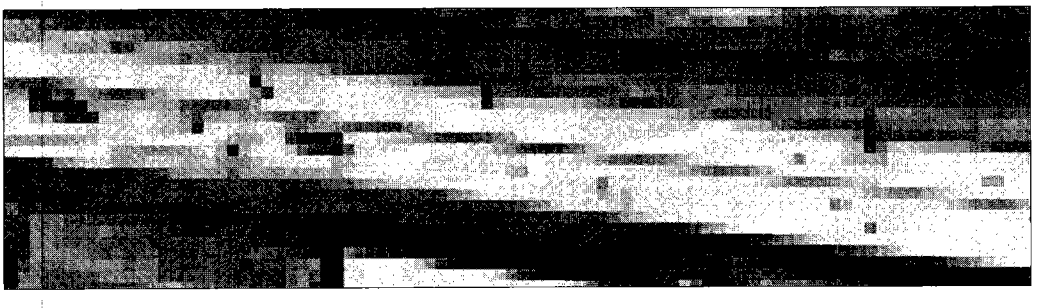
Figure 3: Flowchart of the decision rules for classification of vehicles

Figure 4. Locations of aerial photographs in Franklin County, Ohio

(a) 1 meter simulated resolution



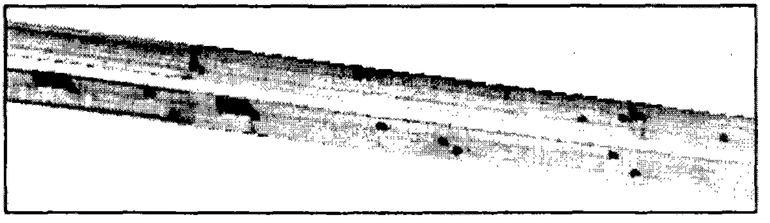
(b) 2 meter simulated resolution



(c) 4 meter simulated resolution

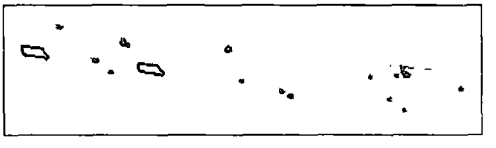
Figure 5. Highway 513 segment at three simulated resolution

(a) Original image

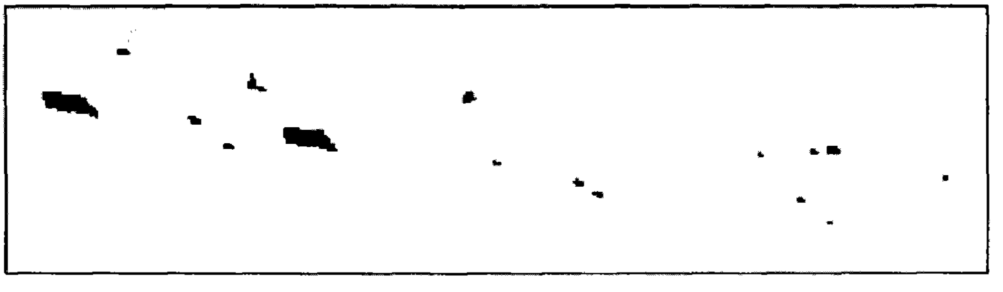


(b) Road extracted image

(c.1) Thresholded image



(c.2) Edge image



(d) Final image with detected vehicles

Figure 6. Representation of intermediate image processing with final image (513)

difference in the appearance of the images. This is due to the fact that the images do not contain much noise. However, for the case of remotely sensed images acquired by satellite, the filtering techniques will most likely improve the images.

The vehicle detection and identification procedure proposed in this research was implemented to seven simulated images with three resolutions. Figure 6 presents a series of processes for one of seven simulated images.

As shown in Figure 6, the final image contains the detected vehicles that are identified and classified as cars and trucks through decision rules. Some of vehicle candidates are eliminated, which does not satisfy the criteria of decision rules. The following two tables show the statistical performance measures for proposed image processing technique.

Table 1. Fraction of vehicles correctly identified

Highway Segments	1 meter	2 meter	4 meter
513	39/40 = 0.975	34/40 = 0.85	16/40 = 0.4
514	42/46 = 0.913	32/46 = 0.696	21/46 = 0.456
753-1	47/48 = 0.979	37/48 = 0.771	25/48 = 0.521
753-2	31/32 = 0.969	29/32 = 0.906	13/32 = 0.406
753-3	31/36 = 0.861	26/36 = 0.722	12/36 = 0.333
791-1	51/55 = 0.927	40/55 = 0.727	24/55 = 0.436
791-2	35/37 = 0.946	28/37 = 0.757	19/37 = 0.514
Aggregate Statistic	276/294 = 0.939	226/294 = 0.769	130/294 = 0.442

Table 2. Fraction of trucks correctly classified

Highway Segments	1 meter	2 meter	4 meter
513	7/7 = 1.000	7/7 = 1.000	7/7 = 1.000
514	9/9 = 1.000	9/9 = 1.000	9/9 = 1.000
753-1	7/7 = 1.000	7/7 = 1.000	6/7 = 0.857
753-2	3/3 = 1.000	3/3 = 1.000	3/3 = 1.000
753-3	8/8 = 1.000	8/8 = 1.000	4/8 = 0.500
791-1	7/8 = 0.875	8/8 = 1.000	4/8 = 0.500
791-2	3/3 = 1.000	3/3 = 1.000	3/3 = 1.000
Aggregate Statistic	44/45 = 0.978	45/45 = 1.000	36/45 = 0.800

As shown in Tables 1 and 2, the image processing method performed well. For example, in the fraction correct statistics, the correctly identified vehicles were 93.9% overall for the 1 m resolution. However, most accuracies for the image processing approach were consistently above 0.90, except for highway segment 753(3). In this case we believe the accuracy dropped to 0.86 because of the varying shades of the pavement that caused confusion with the classifier.

At the 2 m resolution the accuracy dropped to 0.769. We had hoped that a 2-m resolution would be suitable for identifying a car-sized vehicle, but our tests show that we cannot achieve the desired accuracy. At the 4 m resolution, the overall accuracy drops to 0.442. We are able to accurately map the trucks at the 1 and 2 m resolutions (see Table 2). However, at the 4 m resolution, we could only map all of the trucks 4 out of 7 times. In two cases, we were able to map 50% of the trucks and for the remaining segment we were able to achieve an accuracy of 0.857. For this case, if we only had to detect a truck size vehicle, we could use the 2 m resolution.

5. Conclusions

We were tasked to determine the possibility of using satellite remote sensing data to collect highway traffic data. From our image processing tests with several highway segments we could count and classify vehicles at excellent levels of accuracy with 1-m resolution. Based on our tests, we recommend that the resolution from a satellite platform be 1-m to count and classify vehicles.

Before satellite data could be used routinely to count and classify traffic data on an operational basis, the infrastructure required to process and use the satellite data must be considered. The Eyeglass system, which will provide 1-m resolution satellite data, will be launched and operational in 1997. This provides an excellent opportunity to develop the infrastructure required to process and use the satellite data on an operational basis for traffic data collection system.

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