Application of the Image Analysis Technique to Detect Left-Turning Vehicles at Intersections

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This study applies the image analysis technique to detect left-turning vehicles at intersections. The problems existing in the current method of left-turn data collection are discussed. An optical image device system including a CCD video camera, an interface board, an image monitor, and an IBM PC/AT was used. An algorithm with linear time complexity was developed for detecting left-turning movements at intersections. Microcomputer software was derived for the algorithm. This computer system is a real time system. The accuracy of the algorithm is about 80% for detecting the left-turning vehicles whose signal lights are on. This study so far has had only limited success. The difficulties of attaining greater accuracy as well as the possibilities of improving the developed image analysis system are also discussed.

The goal of a traffic system is to provide rapid, economical, and safe movement of vehicles and pedestrians in a city or in an urban area. Since a traffic system works as a circulation system, its operating efficiency will significantly affect the city's growth and economic development. However, intersections probably represent the most critical elements of the traffic system. Since two or more streets share the space at an intersection, the capacity of the intersection is generally limited. One of the main factors which affects the capacity of such an intersection is the presence of left-turning vehicles. Thus, traffic problems such as traffic congestion, fuel consumption, air pollution, and noise pollution have usually occurred at these intersections, particularly when heavy left-turn traffic was present.

Left-turning vehicles cause fewer problems at an intersection under low-volume conditions. As the traffic volume of an intersection approaches capacity, however, fewer opportunities for left-turning maneuvers exist. Both the left-turning vehicles and the non-turning vehicles which queue frequently behind the turning vehicles suffer long delays before clearing the intersection. Thus, drivers sometimes become impatient and make hazardous maneuvers after experiencing long delays at an intersection.

Before making improvements to the traffic system, traffic engineers must have adequate and accurate traffic data. Traffic data can be divided into three types: traffic volumes, vehicle speeds, and intersection delays. These traffic data are important in practice because they may indicate locations where improvements are needed. In addition, these data are used in before-and-after studies to determine the effectiveness of changes in parking prohibitions, signal timing, one-way streets, or turning prohibitions. Furthermore, the left-turn volume during different hours of the day is one of the major criteria for determining these changes. This is because the left-turn volume significantly affects vehicle speeds and intersection delays.

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NEED FOR RESEARCH

Basically, there are two methods for gathering traffic data: manual and automatic. The manual method is labor-intensive. This method requires high labor costs for data collection and data processing, particularly when massive quantities of traffic data are required. In addition, the data collected by an observer is sometimes inaccurate because it is difficult for an observer to keep an eye on a street scene for hours. However, the manual method allows data to be collected on the basis of turning movements and vehicle classifications. On the other hand, the automatic method uses automatic recording devices for gathering field data and further processes these data by using microcomputers. The automatic recording devices include pressure-type road tubes, electrical contact tapes, photo-electric detectors and inductive loop detectors (*1*). The automatic method is able to continuously record and process traffic data for long periods of time. This method is generally more economical and accurate than the manual method.

Today, there is a real need among traffic engineers, not only for more data, but also for data of a more complex nature. Although the automatic method for gathering traffic data has been widely used in major cities, this method has problems in providing left-turn traffic data. These problems are discussed below.

1. No Turning Movement Data: The automatic recording devices are incapable of determining turning movements except for the intersections equipped with exclusive turning lanes. However, the turning movement data are especially significant in design, channelization, lane marking, signal timing, and the application of control devices.
2. Wheel-Oriented Data: The automatic recording devices can only detect the number of wheels passing over the detection devices. Thus, the automatic method provides the num-

ber of wheels for the traffic volume data, and the number of wheel-seconds for the traffic delay data. This type of traffic data may not be suitable for traffic network systems analysis.

This study has reviewed some published literature related to the topics on traffic data collection and the application of image analysis to traffic engineering. The results of the literature review indicate that in the last decade a variety of systems have been developed specifically for traffic data collection and/or monitoring. Dickinson and Waterfall (*2*) provided an excellent review of these systems. They covered the general subject of image processing and the analysis of traffic scenes. They concluded that the hardware and software of the video image system have to be improved in order to provide a general-purpose traffic data collection system.

Branston (*3*) used a time-lapse photography method to collect traffic data on speeds and headways. Garner and Uren (*4*) used a coordinate reader and an electronic computer to reduce the time of data collection and analysis for the aerial photographic method. Mountain and Graner (*5*) provided a review of the types of photography and traffic data that may be collected by using the aerial photographic method. In addition, Ashworth (*6*) and Polus, et al. (*7*) described a video recording system for measuring traffic data such as speeds, occupancies, and volumes. Wootton and Potter (*8*) used video cameras to record traffic movements and the recording was linked to a TV monitor and a microcomputer. Ashworth and Kentros (*9*) used an ultrasonic detector to measure vehicle occupancy.

Since the mid-1970s, the U.S. Department of Transportation has been funding research on image processing applied to freeway surveillance at the Jet Propulsion Laboratory (JPL) in Pasadena. Hilbert, et al. (*10*) in 1978 described the conceptual design for the wide-area detection system (WADS). The major objective of this system is to track individual vehicles within the scene. In order to track the vehicle, they used the cross-correlation method to produce "best-fit" locations for the vehicle in each frame. Thus, traffic data such as speed, acceleration, and lane changing can be estimated. Schlutsmeyer, et al. (*11*) in 1982 described several practical problems with the cross-correlation method for vehicle tracking. These problems include the high computational cost, the difficulties of tracking a vehicle if its gray values changed, and the low accuracy for distant vehicles. Thus, JPL engineers reverted to a simpler approach using a single lane across the traffic lanes and monitoring it to detect any vehicle entering the detection area close to the camera. Then the leading and trailing edge of the vehicle image are located in two frames and the vehicle velocity is calculated subsequently.

Dickinson and Waterfall (*12*) described the development of a multi-microprocessor system for preprocessing video images of traffic scenes. Moreover, Houghton, et al. (*13*) showed that, with suitable reduction of image data and with appropriate feature extraction, several vehicles can be tracked concurrently on a highway network.

In conclusion, the results of the literature review indicate that a variety of systems have been developed for measuring traffic data such as volumes, speeds, headways, lane occupancies, and junction turning counts. However, the detection of left-turning vehicles at intersections is needed.

OBJECTIVES AND SCOPE

Image analysis is one of the subjects in the area of computer vision. An image is a two-dimensional array of pixels, obtained by a sensing device which records the value of an image feature at all points. The goal of image analysis is the construction of scene descriptions on the basis of information extracted from images or image sequences (*14*). Over the past two decades, many techniques for analyzing images have been developed, and this subject has gradually begun to develop on a scientific basis. The main applications of image analysis include document processing, microscopy, radiology, industrial automation, remote sensing, and reconnaissance.

This study intends to determine the feasibility of applying the image analysis technique to solving the problem of detecting left-turning movements. This study also intends to provide engineers with a better understanding of increasing traffic complexity. The specific objectives of this study are:

1. To identify problems and needs associated with the development of automatic traffic data collection and analysis,
2. To determine the suitability of applying the image analysis technique in the area of traffic engineering,
3. To develop an algorithm and a computer program for detecting left-turning vehicles, and
4. To investigate the real time possibility for continuously analyzing images of left-turning movements.

This study does not intend to completely solve the two problems listed previously. Rather, this is a preliminary study to determine not only the suitability of applying the image analysis technique but also the possibility of real time analysis for solving traffic problems. Thus, this study emphasizes the left-turning movements during the daytime only. The left-turning movements at night, as well as the right-turning and through movements, are not included in this study.

METHODOLOGY

Optical Image Device System

In order to conduct this research, an optical image device system was chosen. Figure 1 depicts the structure of the four major items which are included in this image system. These four items are listed below:

1. CCD Video Camera: CCD stands for charge coupled device. The purpose of a CCD video camera for this study is to convert the light energy when taking pictures from the street scene into analog signals.
2. Interface Board: As shown in Figure 1, the interface board is not only an analog-to-digital converter but also a digital-to-analog converter. The interface board converts the analog signals taken from the CCD camera into digital signals which are sent to a computer. In addition, the interface board converts the digital signals stored in the display memory into analog signals to be displayed on an image monitor. A Truevision Advanced Raster Graphics Adapter 8 (TARGA 8) board from AT&T (*15*) was selected for this study.
3. Image Monitor: Through the interface board an image monitor displays not only the live images taken from a CCD

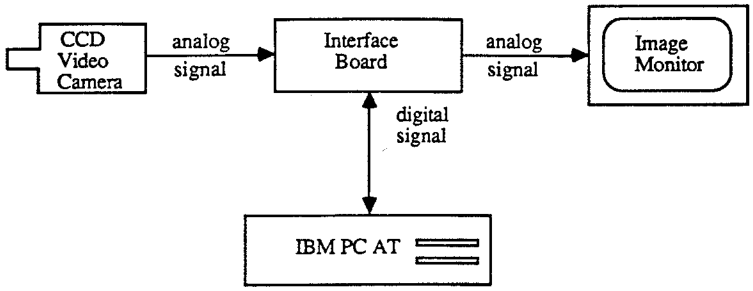

FIGURE 1 The structure of an optical image device system.

video camera but also the images stored in the computer memory. Thus, engineers can visualize the street traffic from the image monitor and make any adjustment if necessary. A black-and-white TV was chosen to be the image monitor for this study.

4. IBM PC/AT Computer: The purpose of an IBM PC/AT or equivalent is to store and/or analyze the digital data of images sent through the interface board. The PC/AT can also send the images stored in the computer memory through the interface board to be displayed on the image monitor. The reasons for selecting a PC/AT are its computing speed and capacity of its hard disk as well as its compatibility to the selected interface board.

Signal Lights of Left-Turning Vehicles

The driver's manuals in Canada state that a driver "should signal his intentions continuously and for a sufficient distance before making a turn" (*16*). The purpose of signaling before making a turn, for drivers in Canada, is the same as in other countries—safety. Thus, the left-turning vehicles which do not signal will be ignored in this study due to the limitations of the proposed method discussed below.

When pictures are taken of left-turning vehicles at intersections during the daytime, the signal lights of left-turning vehicles will likely be the brightest spots on the pictures. This study intends to search for these signal lights of left-turning vehicles in order to detect the left-turning movements. In other words, this study will utilize the image analysis technique to extract the left-turning lights from the pictures. However, "white noise," such as the reflection of vehicles from the sun, makes the search for signal lights difficult to obtain accurately.

Images are built up from individual dots, called picture elements or pixels. The display resolution is defined by the number of the dots in the picture, *i.e.*, by the rows or scan lines from top to bottom and the number of pixels from left to right in each line. The number of rows and the number of pixels in an image are determined by the computer capacity and the interface board.

As stated previously, a TARGA 8 board from AT&T was chosen for this study to digitize and store images. The TARGA 8 board supports an enhanced spatial resolution of up to 512*482 pixels with 256 gray levels (8 bits per pixel), and captures images in real time: 1/30 second per frame. The 256 gray levels range from 0 to 255. The gray value of 0 indicates the dimmest level in an image. When the gray value increases, the brightness level of pixels increases. Thus, the gray value of 255 represents the brightest level in the image. Therefore, this study will extract the spots or clusters in which these pixels have high values of gray levels. For instance, this study may search for the cluster in which most of the pixels have gray values of or above 240.

Figure 2 shows a black-and-white photo of left-turning movements at an intersection. In this picture, there are three left-turning cars whose signal lights are on. This example is to demonstrate what the pixels in an image are and what the gray values of the pixels are. Thus, this photo was digitized by using an optical scanner. The outputs from the scanner are gray levels of the pixels in the image. In order to obtain a hard copy from the computer printer, there are only 16 gray values from the scanner instead of 256 gray values from a TARGA 8 board. These 16 gray values range from 0 to 9, plus A to F. However, in order for human eyes to visualize the objects in the image, the sequence of gray levels has to be reversed. In other words, in this sample, the gray values 0 and F represent the brightest and the dimmest light levels, respectively. It is noticed that, in the TARGA 8 board, the gray values 0 and 255 represent the dimmest and the brightest light levels.

Figure 3 illustrates part of the output from the scanner. This figure includes the first two cars only. The boundaries of the two cars, the background of the scene, and the left-turn lights of both cars are delineated by a black pen. In this figure, the gray values of the hood and side doors for the white car are 0 and for the dark-blue car are D or E. On the other hand, the gray values for the shadows underneath these two cars are E and those for the pavement surface range from

FIGURE 2 An example of left-turning movements at an intersection.

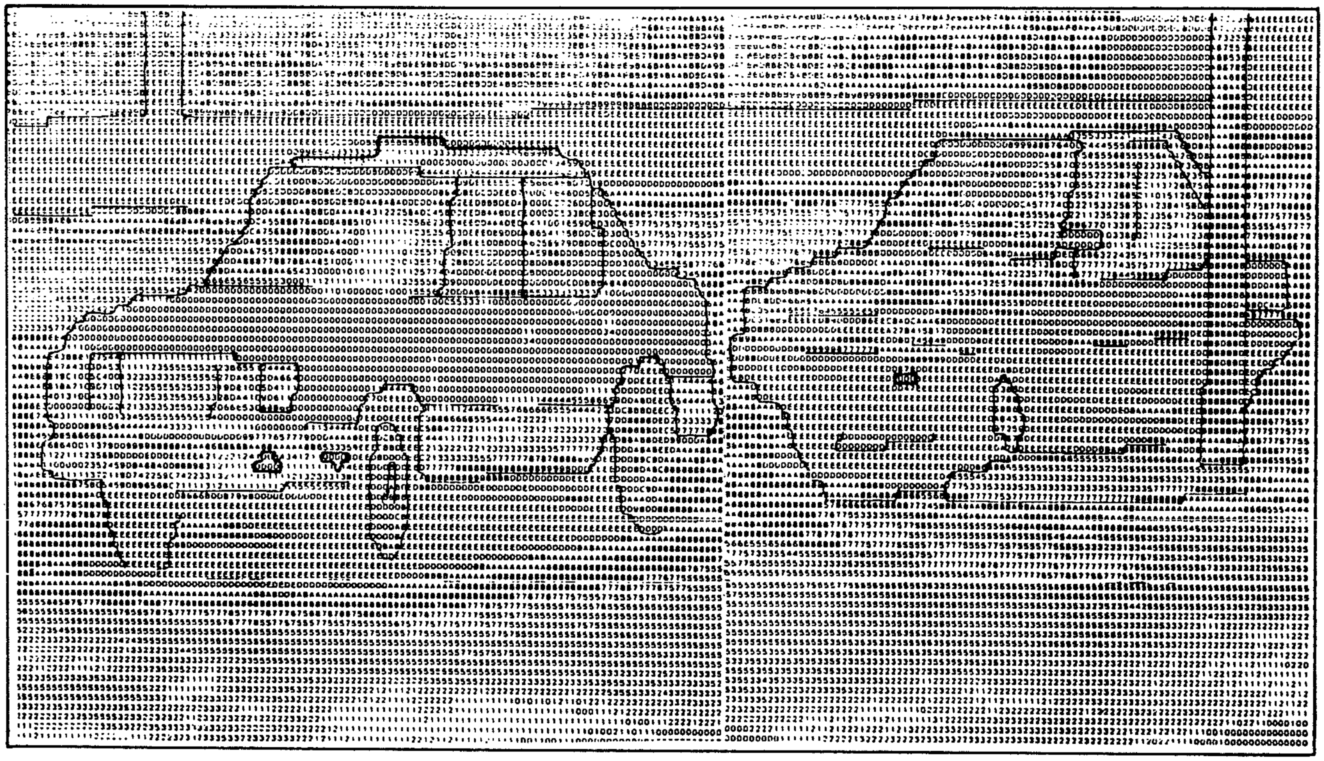

FIGURE 3 The gray values of two left-turning cars.

1 to B. Thus, it is feasible to group an image into several regions which share some values of a feature. Moreover, the gray values of the turning lights for both cars are 0. In addition, the neighborhood of the turning lights has gray values ranging from 1 to 8 for the white car and from 4 to D for the dark-blue car. Thus, the turning lights can be detected by finding bright groups of pixels and the abrupt discontinuities of such an image feature.

Algorithm

This study develops an algorithm to determine the number of left-turning vehicles by detecting their turning signals at intersections. Figure 4 depicts the flow chart of the algorithm. This algorithm is divided into three stages, which are discussed below.

Stage 1: Environment Setting

This stage of the algorithm fetches the relevant portion of traffic images into the RAM (Random Access Memory) of an IBM PC/AT. This stage also predetermines some factors of the environment. The four steps in this stage are as follows:

Step 1: Fetch images from the camera to the TARGA 8 board. In this step, the TARGA 8 board is set in the live mode in order to continuously grab the images taken from a CCD video camera into the display memory on the board.

Step 2: Fetch the relevant parts of the images into the RAM of a PC/AT computer. Here, the relevant parts of the images on the display memory are fetched into the RAM of the PC/AT computer by discarding most of the images' background. The relevant part is the image portion containing the left turning vehicles and their surrounding background. This step significantly reduces the size of the traffic images.

Step 3: Determine the threshold of the bright pixels. In order to extract the pixels with high gray value, traffic engineers have to determine the threshold of the bright pixels, so that the pixels with a low gray value can be masked out in the next stage. From the results of this study, a gray value greater than or equal to 240 should be chosen as the threshold of the bright pixels.

Step 4: Determine the acceptable length of the bright segments. A bright segment is a group of consecutive pixels located in a line. In order to filter out white noise (*i.e.*, tiny bright spots in the image), traffic engineers predetermine the acceptable length of the bright segments. If the length of a bright segment is less than acceptable, then the bright segment is white noise and will be discarded. The acceptable length of the bright segments is the minimum length of the signal lights in the images. The acceptable length mainly depends upon the resolution of the images and the distance from the camera to the left-turning vehicles. Thus, engineers can output the gray values of pixels for several images at the beginning of the data collection. In this way, the length of the signal lights can be estimated.

Stage 2: Image Processing

During this stage, the pixels of the images obtained in stage 1 are scanned in order to locate all bright segments. In the meantime, any new segment will either create a new bright cluster or update an existing cluster. This stage principally

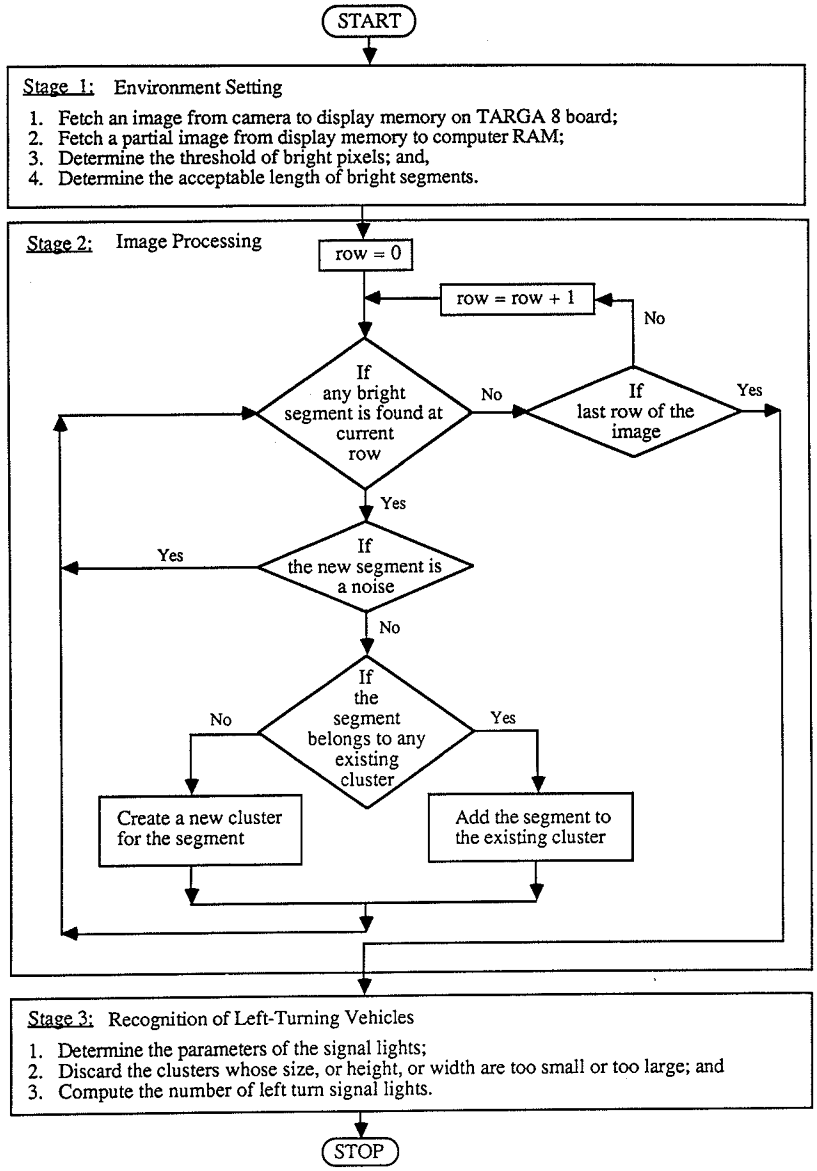

FIGURE 4 The flow chart of the algorithm.

processes the images in order to search for bright clusters, which are likely to include signal lights and other bright objects such as the reflection of vehicles. Four major steps are included in this stage and discussed below:

Step 1: If any bright segment is found at the current scanned row of the image, proceed to step 2. Otherwise, continue to scan pixel by pixel until the end of the row. A bright segment is a group of bright pixels which are next horizontally adjacent in a row of the image. When the present row is scanned pixel by pixel, and if a bright pixel is found, this pixel is considered as the left boundary point of a bright segment. Then, the algorithm searches for the right boundary point of the bright segment. A pixel is considered as a right boundary point if the following two pixels are not bright.

Step 2: This is to be undertaken if the new segment is noise. The length of a new bright segment is equivalent to its number of pixels. Because the two boundary points of the segment are known, the length of the segment can easily be computed. In this step, if the length of the segment is less than acceptable, the segment is considered to be white noise and will be discarded; go back to step 1. Otherwise, proceed to the next step.

Step 3: After a bright segment is confirmed in step 2, step 3 examines the possibility that the segment may belong to an existing cluster. If so, the segment will be added to that existing cluster. Otherwise, a new cluster will be created for this segment.

Figure 5 illustrates the algorithm for determining whether the cluster belongs to any existing cluster. This algorithm does not search every existing cluster for making such a determination. Instead, it ascertains whether the pixels corresponding to this bright segment belong to any existing cluster. In Figure 3, the solid curved line is the boundary for the existing cluster *I*. The boundary is a curved line connecting all boundary points of bright segments. The dashed line is the current scan line, and pixels *a* and *b* are the two boundary points of this

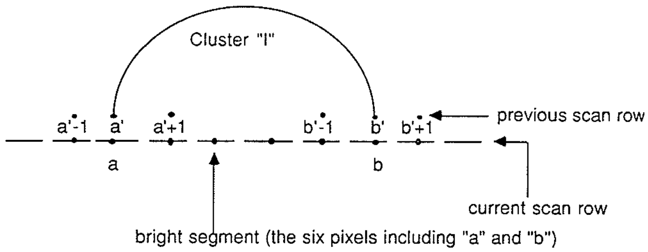

FIGURE 5 The algorithm for checking an existing cluster.

new segment. In addition, pixels a' and b' correspond to a and b, respectively. Pixels $a' - 1$ and $a' + 1$ are the two pixels adjacent to pixel a', as are pixels $b' - 1$ and $b' + 1$ adjacent to pixel b'.

Since the images obtained by the TARGA 8 board are high resolution, with about 20K pixels per image, any bright object in the image will have a smooth boundary line. Therefore, this algorithm checks if any of pixels $a' - 1$, a', and $a' + 1$, or any of pixels $b' - 1$, b' and $b' + 1$ belong to an existing cluster. If so, the new segment belongs to the same cluster. If not, a new cluster will be created for the new segment. For instance, in Figure 3, pixels a', $a' + 1$, $b' - 1$, and b' belong to cluster I. Thus, the new cluster, with the two boundary pixels a and b, belongs to cluster I.

Step 4: This step checks if the current scanned line is the last row of the image. If so, proceed to stage 3: this means that the current image has been completely processed. Otherwise, scan the next row of the image and go back to step 1 of this stage.

Stage 3: Recognition of Left-Turning Vehicles

This stage sets up three parameters in order to search the obtained clusters for recognition of the left-turn signal lights of vehicles. This stage includes three steps, as follows:

Step 1: Determine the parameters of the signal lights. The bright clusters obtained from stage 2 include left-turn lights and other bright objects such as the reflection of vehicles from the sun. This step sets up three sensitive parameters for every cluster in order to distinguish left-turn lights from the other bright objects. These three parameters are size, width, and height of a cluster. The size of a cluster is the number of pixels contained in that cluster; the width of a cluster is the number of pixels for the longest row in that cluster; and the height of a cluster is the number of pixels of the longest column in that cluster. However, the results of this study indicate that the parameter of size is the most sensitive among the three parameters.

Step 2: Discard the clusters whose values of parameters are not within the acceptable range. Traffic engineers have to predetermine the acceptable range for each parameter, which depends on the resolution of the images and the distance from the camera to left-turning vehicles. In order to predetermine the acceptable range, engineers can output the gray values of several images of traffic scenes. The size, width, and height of all signal lights are counted. Thus, the acceptable range for each parameter is between the lower bound and upper bound of each parameter. This step checks the parameters of each cluster to determine if the values of the three parameters fall into the three acceptable ranges, respectively. Since the size parameter is the most sensitive, the sequence for checking is (a) size, (b) width, and (c) height. So, if the size of a cluster is out of the acceptable range, the cluster will be discarded immediately, and it will not be necessary to check the other two parameters.

Step 3: Compute the number of left-turn lights. After Step 2 is completed, the clusters remaining are left-turn lights. This step counts the number of clusters for estimating the number of left-turning vehicles.

Time Complexity of the Algorithm

Intuitively, the time complexity of an algorithm is the required running time of the algorithm when solving a problem. When an algorithm manipulates data, the manipulation can be broken into many elementary operations or groups of elementary operations, such as comparisons, additions, and multiplications. Thus, the time complexity of the algorithm is defined as the total number of operations for processing input data and producing output information when solving the problem.

Let $T(n)$ denote the time complexity of an algorithm where n is the size of the input data of a problem. This is because $T(n)$ is usually a function of n. The big-O notation is also used to describe the relationship between $T(n)$ and n. This relationship is a good indicator in evaluating the effectiveness and the power of an algorithm. For instance, if an algorithm with $T(n) = O(n^2)$, this indicates that the upper bound of the computer time increases as a square when the size of the problem increases. If an algorithm with $T(n) = O(n^3)$, it means that the upper bound of the computer time increases cubically when the value of n increases. Obviously, the algorithm with $T(n) - O(n^2)$ is superior to the algorithm with $T(n) - O(n^3)$. This is because the former algorithm requires less computer time than the latter when n is sufficiently large. Furthermore, the latter algorithm becomes extremely expensive, even computationally unfeasible, (compared to the former algorithm) when solving a huge problem.

The purpose of this section is to prove that the

$$\text{Time Complexity of the Proposed Algorithm} = O(n)$$

where n is the size of an image. The size of an image is represented by the number of pixels in this study. The time complexity of the algorithm is analyzed according to the three stages discussed below.

Stage 1: Environment Setting. In this stage, the algorithm digitizes the image from the camera, stores the digitized image in the display memory of the TARGA 8 board, and then grabs the relevant part of the image from the display memory to the computer RAM. The required computer running time in this stage is linear (Note: This statement has been verbally confirmed by AT&T.). Thus, the time complexity of stage 1 of the algorithm is $O(n)$, when n is the number of pixels of the image.

Stage 2: Image Processing. This stage horizontally scans each row of the image pixel by pixel to locate all the bright segments on the current row. If a bright segment is found, the algorithm makes one comparison to determine if the segment is white noise. If the segment is not white noise, the algorithm makes at most six comparisons to determine if the segment belongs to any existing cluster. Therefore, the time complexity of this stage is $O(n)$.

Stage 3: Recognition of Left-Turning Vehicles. Let m denote the number of bright clusters. In this stage, the algorithm needs at most three comparisons for each cluster to determine if the cluster is a left-turn light. These three comparison are the three parameters (i.e., size, width, and height of the cluster). Thus, the time complexity of this stage is $O(m)$. However, $m < n$ is true. Therefore, the time complexity of this stage is also $O(n)$.

In conclusion, the time complexity of the proposed algorithm is $O(n)$ where n is the number of pixels per image. This indicates that the upper bound of the computer time increases proportionally to n when the size of the images increases. This also indicates that the algorithm is efficient and powerful.

EXPERIMENTAL DESIGN AND ANALYSIS

"Left-Turn Detection" Software

Using the derived algorithm, this study has developed microcomputer software, named "Left-Turn Detection." The main objective of this software is to detect left-turning vehicles at intersections. This software uses a DOS 3.1 operating system for IBM PC/AT computers. This software was written in the C computer language. The C language is suitable for this study because it can manipulate bits and is compatible with the TARGA supporting software (*17*) provided by AT&T.

Left-Turn Detection software utilizes a C86 compiler from Computer Innovations Inc. Because an image file can take up to 256K-byte memory space, the default value for stack and heap is changed to 320K-bytes. In order to speed up the program, this study takes advantage of the 80286 microprocessor by switching the compiler option to 80286 (the program will only run on 80286 microprocessors). Furthermore, the running time of this software is linear, i.e., the running time is proportional to the size of the input image file. This is the best feature of the program, that it conforms to a real time computer system.

Real-Time Analysis

The application requires a real time system. This means the response time of the computer system has to be tied to the time scale of events occurring outside the computer. The computer must be able to accumulate, process, and output data within a critical, specified time period. In order to accomplish the real time analysis, this system requires guaranteed response from each part of the computer system—peripherals, processor, operating system, and the users' program—since the time headway of left-turn vehicles approaching an intersection is about 2 seconds per left-turn lane during peak hours. Thus, if the computer system can capture, process, and output the result within one second, the system is a true real time system for this study.

The TARGA 8 board takes up to just 1/30 second to capture an image from a video camera to the display memory of the board. The required computer time is small because of the memory arrangement known as Row Addressable RAM (RARAM): a scheme that enables a row of 4000 bits to be moved into the memory at once, instead of 1 bit or 1 byte at a time. By using the same memory management, the image is transferred from the display memory of the TARGA 8 board to the memory of the IBM AT.

The image in RAM is processed by the algorithm. As discussed previously, the complexity of the algorithm is linear, *i.e.*, if the image has n bytes, then the running time is $O(n)$. The second stage of the algorithm has to go through the memory location byte by byte to process the image. This processing takes longer than the transferring. For example, if the algorithm processes 20K bytes, then for every byte the memory access time would be around 5×10^{-5} seconds and the total computer time would be about 1 second.

In order to investigate the possibility of real time analysis, left-turning movements were tape-recorded by using a CCD video camera at the intersection of Sherbrooke and St. Mathieu Streets in downtown Montreal, Quebec. Thirty images of left-turn movements from different cycles of traffic signal timing were selected randomly for conducting this experiment.

The conditions of the experiment were as follows:

1. The images are black-and-white, and the gray level of each pixel ranges from 0 to 225;
2. After the preprocessing procedure in stage 1 of the algorithm, each image has 80 rows and every row has 256 pixels (*i.e.*, each image has about 20K pixels);
3. The microprocessor used is Intel 80286; and
4. The threshold of gray level to distinguish bright pixels from the images is 240.

These thirty images were input into the Left-Turn Detection Software for detecting left-turning movements. The average running time for these thirty samples was 0.85 seconds. The standard deviation for this average value is 0.09 seconds. Thus, the algorithm is able to complete the analysis of an image within 1 second. Furthermore, the time for capturing an image and sending it to the RAM of the IBM PC/AT is about 0.05 seconds per image. This computer time is controlled by the TARGA 8 board. Hence, the total average computer time for each image is about 0.90 seconds. It is still less than 1 second. Therefore, the computer system developed is a real time system.

One second of computer time is a desirable amount of time to analyze an image on the basis of real time study for the intersection with one left-turn lane at each approach. Thus, a fraction of 1 second may be the time limit for the intersections with two exclusive or mixed left-turn lanes at each approach. Since the Intel 80386 processor is about two to three times faster than the Intel 80286 processor, by using the 80386 processor a real time computer system for this study can still be achieved.

Accuracy of the Algorithm

The same thirty images of left-turning movement were also chosen to determine the accuracy of the algorithm in detecting left-turning vehicles at intersections. The set of samples was taken from a mixed left-turn and through lane at a busy intersection during peak hours on sunny weekdays. These thirty images showed the different combination of cases in vehicle types, vehicle makers, number of vehicles in the queue, and percentage of left-turning vehicles in the queue. These images were input to the Left-Turn Detection software. The results of the computer output were compared with the results of human observation on an image monitor. The comparison indicates that the accuracy of the algorithm for these thirty images was about 80% for detecting the left-turning vehicles whose signal lights were on. Since not every driver uses turning signal lights, the reliability of the algorithm is further reduced.

The 80% accuracy indicates that the developed image analysis system has not reached the implementable stage yet. Improvements in both hardware and software are needed for the developed system. However, the difficulties of attaining greater accuracy are discussed below:

1. Reflection of Small Objects: The first stage of the algorithm has discarded most of the background, such as buildings and sidewalks, as well as the through vehicles in the adjacent lanes from the image. Thus, there are about 20K pixels remaining in each image in the second stage of the algorithm. These partial images still contain many objects. On sunny days, objects such as headlights, bumpers, windshields, windows, roofs, frames, wheel covers, and door handles on the vehicles all reflect sunlight into the camera. Thus, the bright clusters in the second stage of the algorithm include signal lights of vehicles plus all kinds of reflection. The third stage of the algorithm intends to distinguish the reflections from the signal lights by examining the size, width, and height of the cluster. However, it is extremely difficult for the algorithm to delete the reflections with sizes and shapes similar to those of the signal lights.
2. Variation of the Size of Signal Lights: There are two factors affecting the variation of the size of the vehicle signal lights. They are the size of the vehicle itself and the distance of the vehicle light from the camera. The size of the signal lights varies according to vehicle size and manufacturer. In general, large cars have larger signal lights than small cars, and European cars have slightly larger lights than Japanese and domestic cars. In addition, trucks, buses, and trailers have different sizes of signal lights among themselves and in contrast to other passenger cars. Furthermore, the longer the distance of a vehicle from the camera, the smaller the size of the lights present in the image. In other words, the queue position of the vehicles significantly affects the size of the signal lights shown in the image. Due to the wide variation in sizes, it is difficult for the algorithm to recognize the signal lights accurately.
3. Blinking of the Lights When Turned On: From observation, signal lights of vehicles blink from fifteen to twenty times every 10 seconds when the lights are on. The blinking of lights affects not only the size of the lights but also the gray values of pixels of the lights. The effect of blinking has made it even more difficult to detect the left-turn movements.

The possibilities for improving the developed image analysis system are as follows:

1. Hardware Aspect: A color interface board such as TARGA 16 will be recommended. TARGA 16 requires 2 bytes to present every pixel. For every pixel in TARGA 16, 5 bits are assigned to each of the primary colors (*i.e.*, red, green, and blue). Thus, TARGA 16 can display about 32,000 different colors. Since the color of signal lights of vehicles is yellow, it would be a great incentive in solving the problems listed above to examine the color of bright clusters. However, the disadvantage of using TARGA 16 is that the size of the images stored in the computer is larger than that in the TARGA 8, and thus more computer time is required.
2. Software Aspect: The third stage of the algorithm has to be modified. To solve the problem of the blinking lights, two or three consecutive images will be compared to determine the number of left-turning vehicles. Furthermore, a new parameter in the shape of the cluster might also help distinguish the lights from the reflection of small objects. The parameter, or shape of the cluster, is the combination of the two parameters, width and height of the cluster.

CONCLUSIONS

Image analysis is one of the subjects in the area of computer vision. The image analysis technique includes two main procedures: image processing and pattern recognition. This technique has been successfully applied to several areas, such as document processing, microscopy, radiology, industrial automation, remote sensing, and reconnaissance. This study intends to detect the left-turning movements at intersections using the image technique. An optical image analysis system—including a CCD video camera, interface board, image monitor, and an IBM PC/AT—was used to conduct this research. The conclusions drawn from this study are as follows:

1. The problems in the current method of left-turn data collection are that there is no turning movement data and no wheel-oriented data.
2. An efficient and powerful computer algorithm was developed for this study. The algorithm includes three stages: environment setting, image processing, and recognition of left-turning vehicles.
3. The developed algorithm has been proven as linear. In other words, the time complexity of the algorithm $T(n)$ equals $O(n)$ where n is the size of the image.
4. Software called "Left-Turn Detection" was developed for IBM PC/AT's. This software was written in the C computer language.
5. The computer system developed for detecting left-turning movements is a real time system. The average computer time for the Left-Turn Detection software to analyze an image is 0.85 seconds. The computer time to grab an image from the camera to the computer RAM is 0.05 sec. Thus, the total average computer time for each image is about 0.90 sec. Hence, this computer system is capable of detecting left-turning movements on a real time basis.
6. The accuracy of the algorithm is about 80% for detecting left-turning vehicles whose signal lights are on. Some improvements in both hardware and software are needed in order to reach the implementable stage in the near future.

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