

Vehicle Reidentification Using Multidetector Fusion

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Abstract—Vehicle reidentification is the process of matching vehicles from one point on the roadway (one field of view) to the next. By performing vehicle reidentification, important traffic parameters including travel time, travel time variability, section density, and partial dynamic origin/destination demands can be obtained. Field traffic data were collected in Alton Parkway in Southern California for training and testing of the multidetector vehicle reidentification algorithm. These data consisted of inductive loop signatures of vehicles that traversed two detector stations spanning a section of an arterial and the corresponding video of these signatures. Even though the video collected was not optimized for pattern-recognition purposes, an investigation into the feasibility of fusing inductive vehicle signatures with video for anonymous vehicle reidentification was conducted. The resulting reidentification rate of over 90% shows that this approach merits further investigation. The results also show that the use of detector fusion provides system redundancy and yields slightly better results than the use of a single detector.

Index Terms—Detectors, fusion, image sensors, surveillance, transportation.

I. INTRODUCTION

EVEN WITH the tremendous increases in computation power since the advent of digital computers and the incredible advances in surveillance technology, the world of traffic surveillance and control has yet to feel their full effect. The field of intelligent transportation systems (ITS) seeks to improve the current state of our transportation system by harnessing our increased communications, processing, and detection capabilities. There is great need for advanced surveillance capabilities to complement the rapid deployment of ITS strategies. This paper presents the results of an initial investigation into the potential of multidetector fusion for intelligent surveillance. Specifically, the focus is to study vehicle reidentification, which is the task of matching a vehicle signal detected at one location (upstream) with the signal generated by the same vehicle detected at a downstream location at some later time. To perform the task at hand, different features that can distinguish one vehicle from another are derived from the detected signals. Identification is performed using a nearest neighbor classifier and a linear fusion strategy. The fusion of

multiple detector signals is shown to improve vehicle-reidentification accuracy slightly and provides system redundancy.

In this investigation into the feasibility of using multidetector fusion for traffic surveillance, a feature based on color information from video cameras is used to augment the inductive signature feature obtained from inductive loop detectors. Inductive signatures are unique deviations in the inductance of a loop detector caused by the passage of a vehicle. Inductive loop detectors are prevalent in many cities all over the world. This investigation using color from video is performed for the following reasons:

- video cameras and video detection are becoming increasingly more popular;
- color information is not correlated with inductive signature information;
- color can be extracted from imperfect video images while more detailed characteristics are more difficult to derive;
- color can be verified visually;
- color can be used with signature information to increase reidentification accuracy.

Since this investigation is performed using video footage that is not optimized for vehicle reidentification and noncalibrated loops, better results can be expected in the future with the use of improved video imaging and loop detection.

One motivation for performing vehicle reidentification is to address the need for section measures of traffic performance. The state-of-the-practice in traffic surveillance involves the measurement of point traffic parameters only. Point measures are those obtained at a particular point on the roadway, while section measures are those obtained for a section of the roadway. Point parameters such as flow and occupancy are measured over the distance of a traffic detector's field of view (FoV), which is usually around 2 m (6.6 ft). Traffic engineers and travelers, on the other hand, require information about entire sections of roadways. For further discussions on the differences between point and section measures, see [1]–[5].

The practical traffic applications of vehicle reidentification are many. The derivation of section travel times (time taken by a vehicle to go from one point to another) is useful to transportation engineers for traffic operations, planning, and control. The method of floating car studies is comparatively more labor intensive and only produces mean or median travel times instead of travel time distributions, which are useful in studying safety and travel time variability. Accurate travel times and densities can be instrumental in travel reliability, feedback control, vehicle routing, traffic assignment, origin/destination demand estimation, and traveler information systems. If vehicles are tracked along consecutive points, then partial origin/destination demands can even be measured instead of estimated.

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The potential benefits of multidetector fusion are many even when cost and complexity are considered. Some of the potential benefits presented by Waltz and Llinas [6] are robustness, extension of temporal and spatial coverage, increased statistical confidence, reduced ambiguity, improved accuracy, increased resolution, and enlarged measurement space.

The improvements related to measurement performance are especially critical for the purpose of vehicle reidentification, since extreme accuracy is desirable (i.e., close to 100% reidentification rate). This is of interest for the derivation of partial origin-destination demands, since vehicles are reidentified over multiple sections of roadway and errors can have a cumulative effect. Also, for closed sections of roadways, the derivation of section density (number of vehicles on a section of roadway at a particular instance of time) requires a high reidentification rate to measure the initial density, which cannot be obtained by using input and output flow differentials.

The miniaturization of detection hardware is also making the packaging of multiple detectors possible. The cost of detectors has decreased significantly, especially if off-the-shelf versions of the detectors are used for eventual implementation. If multidetector fusion systems receive wider acceptance, then the price will decrease further because of increased production volumes. With the doubling of computation power every two years [7], the processing requirements for signal processing and communications should be feasible even for large transportation networks.

II. LITERATURE REVIEW

The technologies for detection of native vehicles (i.e., without additional in-vehicle instrumentation) include inductive loop, video, infrared, ultrasonic, microwave, acoustic, magnetic, road tube, and piezoelectric [8]–[12]. Most of these technologies are made to output point measures that are commonly used by transportation engineers such as volume or counts, point speed, presence, or occupancy. However, there are no technological reasons why these detectors cannot output more information or even raw images of vehicles for the purpose of deriving section measures. One class of techniques that yield section measures uses point measures and stochastic traffic-flow modeling. One such example is Dailey's use of cross-correlation for measuring the propagation time of traffic [13]. Another is Petty's use of the assumption of equal probability distribution [14].

Another class of techniques for obtaining section measures involves vehicle reidentification or the matching of vehicle signatures that come from locations along road sections. Vehicle reidentification can be accomplished by matching individual vehicles or platoons (groups) of vehicles. Some algorithms match individual inductive loop signatures from vehicles by correlating such signatures from two contiguous sites [4], [15]. One traditional method of vehicle reidentification is license plate matching [16].

It also is important to mention that there are systems for obtaining section measures that do not require vehicle detector feature extraction and analysis. Such systems employ in-vehicle beacons that allow system-wide tracking of such vehicles. Such system can include global positioning system (GPS)/cellular modem, toll tags, or other tracking beacons in vehicles and the associated infrastructure for collecting the position of

the vehicles. There have been significant efforts in Asia, Europe, and North America, both academic and commercial, in the area of video image processing for deriving traffic information. Many of these efforts involve either tripwire systems or tracking vehicles within a camera's FoV. Since these systems do not focus on vehicle reidentification, the methods in [17]–[21] are given as few examples out of a vast array of productive video image-processing research. Some of these efforts were part of the FHWA Traffic Surveillance and Detection Technology Development (TSDTD) Program that was managed by the Jet Propulsion Laboratory, Pasadena, CA [22].

Directly related to our efforts in vehicle reidentification is work on matching color from vehicle images conducted by Massachusetts Institute of Technology (MIT)/Northeastern University [23]. The aforementioned Autocolor system uses vehicle color samples modeled as a color histogram, road color samples (for illumination compensation), time of detection, and time windows based on mean and variance of travel time for vehicle reidentification. Our system uses similar color information, but augments the system with inductive loop signatures. Another video reidentification system is V^2 SAT [24], which uses video signature vectors (VSV) composed of physical lengths delineated by abrupt intensity and chromatic changes along a vehicle's centerline. This system requires an overhead (down-looking) camera placement above individual lanes, which is different from our side/rear angle camera configuration.

In addition to inductive loops and video, there also are other detector technologies that have been used for vehicle reidentification, including laser profiles [25] and weigh-in-motion (WIM) axle profiles [26]. In contrast to individual vehicle reidentification, there are systems for matching platoons or groups of vehicles. Some examples of platoon matching are Coifman's matching of sequences of vehicle lengths derived from loop detectors [27] and Yokota *et al.*'s platoon matching of ultrasonic large vehicles in free-flowing and congested traffic [28].

An important motivation of this paper is to overcome the limitation of using only information from one kind of detector. When inductive loop signatures are used, vehicles of the same model or even different models on the same body frame (metal composition) can be mismatched. The color information from video images can be sensitive to changes in illumination. To improve upon the vehicle reidentification system, fusion of inductive and video data is investigated in this paper.

The literature on multisensor fusion is extensive since it covers so many applications ranging from military to medical. Two helpful and frequently referenced sources on this subject are Waltz and Llinas [6] and Hall [29]. Some recent applications of multisensor data fusion are listed here to show the diversity of this field. These applications include image fusion [30]–[32], cyberspace intrusion detection [33], tracking and target recognition [34], [35], machine monitoring [36], medical [37], traffic management [38], handwriting recognition [39]–[41], and speaker recognition [42]–[44]. A good reference on data fusion in the area of ITS is [45]. There are several important societies that actively promote research in multisensor data fusion, including the Institute of Electrical and Electronics Engineers (IEEE), the International

Society for Optical Engineering (SPIE), Military Operations Research Society (MORS), and societies with a division on C³MIS (command, control, communications, and management information systems).

In terms of multisensor algorithms for identity estimation, Waltz and Llinas [6] provide a good overview of three types of algorithms; namely, physical models, cognitive-based models, and parametric classification. Physical models seek to model the observed data and can involve estimation using Kalman filtering or least squares or the use of syntactic components to describe objects. The cognitive-based models seek to replicate human processing. Such models can utilize logical templates, expert systems, or fuzzy set theory. Parametric methods are generally divided into two camps: statistical or information theoretic. Statistical algorithms include Bayesian, classical, and Dempster–Shafer. Decision theoretic algorithms include parametric templates, clustering, neural networks, voting, and entropy.

In terms of decision theoretic approaches, fusion is the combination of different sources of information with the aim of arriving at a decision. Within the context of this paper, fusion comprises the combination of distances obtained using a set of features. Each distance is usually calculated as either the accumulated L1 or L2 distortion from a particular feature (vector or scalar) of a downstream vehicle platoon to that of a candidate upstream vehicle platoon. A set of distances are obtained from an ensemble of features. Feature fusion is the combination of these distances to obtain an overall distance. The decision is based on the platoon that achieves the smallest overall distance (nearest neighbor classifier). Classifier fusion comprises a combination of scores (such as distortions, class labels, or probabilities) using one feature and different classifiers. For fusion to be successful, it is desired that the errors made due to one feature (in feature fusion) or made by one classifier (in classifier fusion) are corrected by using other features or classifiers. If all the features or classifiers are in agreement in making an error, then no combination will rectify the error. However, as long as there is some degree of uncorrelation among the features or classifiers, performance can be improved with the proper combination. This motivates the use of color and inductive signatures, which indeed are uncorrelated. The selection of data fusion techniques can be subdivided based on the type of information that will be combined. For example, if the outputs are distances or probabilities, then methods such as linear or log-opinion pools can be used [39]. If classifier fusion is used and the outputs are actually class labels, then methods such as voting [40] or ranking [41] can be used. For fuzzy decisions, Dempster–Shafer theory can be used for score combination [40]. In this paper, experimental results based on only linear feature fusion are presented.

The linear opinion pool is a commonly used fusion technique that is convenient due to its simplicity. The linear opinion pool is evaluated as either a weighted sum of distances (feature fusion) or scores (classifier fusion). The equation is given by

$$D_{\text{linear}} = \sum_{i=1}^n w_i d_i \quad (1)$$

where n is the number of features or classifiers, w_i is the weight assigned to the i th feature or classifier, d_i is the score for the i th

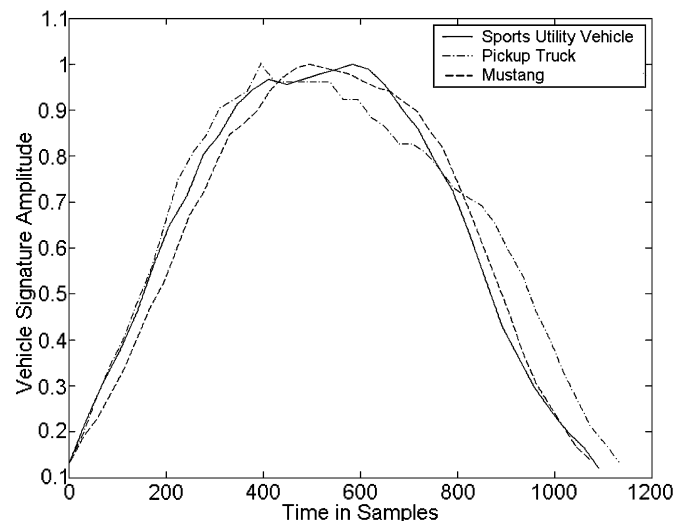


Fig. 1. Examples of vehicle signatures of a sports utility vehicle, a pickup truck, and a Ford Mustang (a car).

classifier or distance for the i th feature, and D_{linear} is the combined classifier score or overall feature distance due to linear fusion. The sum of the weights w_i is normalized to 1.

The linear opinion pool has been evaluated with several applications, such as speaker recognition [42]–[44]. We use the linear opinion pool for vehicle reidentification. The coefficients w_i are determined by searching an n -dimensional grid of real numbers and finding the optimum combination that gives the best performance on the training data alone. The resolution used for this is 1/200. This optimum weight combination is used for the test data.

III. FEATURE EXTRACTION

In this section, a description of six features that are used is given. The first feature is the vehicle signature itself (denoted as s). For both the upstream and downstream locations, there are two inductive loops, each recording a signature. Since the two signatures are almost identical, only one is used for vehicle reidentification. The chosen vehicle signature vector is transformed to be speed invariant and is reinterpolated as equally spaced samples of the original acquired signature. The second feature is the magnitude of the vehicle velocity v (a scalar feature) and is computed as the distance between the two inductive loops divided by the turn on times of the two loops. The third feature is the platoon traversal time p (a scalar). The quantity p is the difference between the time the last vehicle in the platoon crosses an inductive loop and the time the first vehicle in the platoon crosses the inductive loop. Another scalar feature m denotes the maximum inductive amplitude of the vehicle signature before it is normalized. This variable is inversely proportional to the cube of the distance of the vehicle undercarriage to the ground. Therefore, m is correlated with the height of the vehicle suspension. The scalar feature l stands for the electronic length of the vehicle. This value differs from the physical length of the vehicle because it includes the length of the magnetic field generated by the loop and also because it only measures the length of the metallic components of the vehicle that would disturb the magnetic field. Fig. 1 shows examples of the vehicle

signatures of three different types of vehicles; namely, a sports utility vehicle, a pickup truck, and a Ford Mustang (a car). The differences in the signatures allows for reidentification.

Instead of using every possible red–green–blue (RGB) triplet, the colors are quantized or grouped into subsets as a color vector. Pixels with colors that are in the neighborhood of each other are grouped into a single triplet. This process helps to improve reidentification accuracy, since the aggregated space is more tolerant to noise. Quantization of the RGB values to a level of 5 (i.e., each pixel ranged in value from 0 to 4) gave the best reidentification accuracy. Quantization levels up to 30 were tested.

IV. FUSION AND CLASSIFICATION APPROACH

This section gives an overview of the multidetector fusion vehicle reidentification algorithm. The algorithm starts by selecting a platoon detected at the downstream site. A list of upstream candidate platoons are generated subject to a time window constraint that eliminates platoons that are not within a reasonable time frame. Each upstream platoon is then compared with the downstream platoon. A linear minimum L1 (absolute distance) nearest neighbor classifier is used in determining the “best match.” In other words, the upstream platoon candidate that most closely resembles the downstream platoon is selected. The classifier uses the feature vectors described in the previous section and a linear fusion strategy. Because there is a one-to-one correspondence between the individual vehicles of the upstream and downstream platoons, the results from this minimization yield individual vehicle reidentifications. Therefore, individual vehicle are tracked from point to point and vehicle travel times are measured.

The L1 distance measure between an upstream feature f_u and downstream feature f_d is given by

$$d(f_u, f_d) = \sum_{i=1}^q |f_u(i) - f_d(i)| \quad (2)$$

where i denotes the i th component of the feature vector and q is the vector dimension. From Fig. 1, it is observed that the number of components of the signatures may be different for different vehicles. In this case, the vector with fewer components is padded with zeroes before taking the L1 distance. If the size of the platoon is denoted as N_p , the L1 distance for the overall platoon D_p is

$$D_p \sum_{j=1}^{N_p} d(f_u^j, f_d^j) \quad (3)$$

where f_u^j and f_d^j are the upstream and downstream features for vehicle j . Fusion of the six features is performed to get an overall fusion distance D given by

$$D = w_s \sum_{j=1}^{N_p} d(s_u^j, s_d^j) + w_c \sum_{j=1}^{N_p} d(c_u^j, c_d^j) + w_v \sum_{j=1}^{N_p} d(v_u^j, v_d^j) + w_m \sum_{j=1}^{N_p} d(m_u^j, m_d^j) + w_t \sum_{j=1}^{N_p} d(t_u^j, t_d^j) + w_p d(p_u, p_d) \quad (4)$$

where w_s is the fusion weight applied to the vehicle signature distance, w_c is the fusion weight applied to the color information feature distance, w_v is the fusion weight applied to the ve-

locity feature distance, w_m is the fusion weight applied to the maximum inductive amplitude feature distance, w_l is the fusion weight applied to the electronic length feature distance, and w_p is the fusion weight applied to the platoon traversal time feature distance. As before, the subscripts u and d refer to upstream and downstream, respectively. Also, the superscript j refers to the j th vehicle in the platoon. Note that the platoon traversal time feature applies to the entire platoon and not for any individual vehicle. The fusion weights add up to one and are determined during training by searching an n -dimensional grid of real numbers and finding the optimum combination that gives the best performance on the training data alone (as described at the end of Section II). This fusion strategy is known as linear fusion. The distance D between each candidate upstream platoon and a detected downstream platoon is computed. The upstream platoon that achieves the smallest D is matched to the downstream platoon.

Given a downstream platoon, the time window constraint to determine the candidate upstream platoons is described as follows. The time window constraint is applied to each individual vehicle and is used to eliminate upstream vehicles with unreasonable travel times. The upper and lower bounds of the time window constraint, namely, U_t and L_t , are defined as

$$U_t = t_{ld} - t_{\min} \quad (5)$$

and

$$L_t = t_{fd} - t_{\max} \quad (6)$$

where t_{\min} and t_{\max} are the minimum and maximum vehicle traversal times based on the training set, t_{ld} is the travel time for the last vehicle from the downstream platoon, and t_{fd} is the travel time of the first vehicle from the downstream platoon. Each feasible upstream vehicle will need to have a travel time that is greater than L_t and less than U_t . If the number of feasible upstream vehicles is defined as N_v and N_f is defined as the number of feasible upstream platoons, then $N_f = N_v - N_p + 1$. For example, if $N_v = 10$ and $N_p = 3$, then there would be eight consecutive upstream platoons of three vehicles that need to be examined. Then, the distance described in (4) needs to be computed eight times to find the upstream platoon that best matches the downstream platoon.

In this initial development of the platoon reidentification algorithm, the two lanes of traffic were treated separately. This is due to several reasons. First, this is a simpler case upon which more complicated scenarios such as overtaking can be added. Second, if vehicles are not required to be sequential in a platoon, then the problem becomes a combinatorial problem and the solution becomes more computationally intensive. Third, on certain short stretches of roadway, lane changes are infrequent. The test data used is from such a site and the number of lane changes amounted to only 2% of the traffic.

V. DESCRIPTION OF DATA COLLECTION AND IMAGE PROCESSING

The traffic data used for this experiment were collected on June 30, 1998, in Irvine, CA. Fig. 2 shows a diagram of the arterial data collection site. This site consisted of two detector

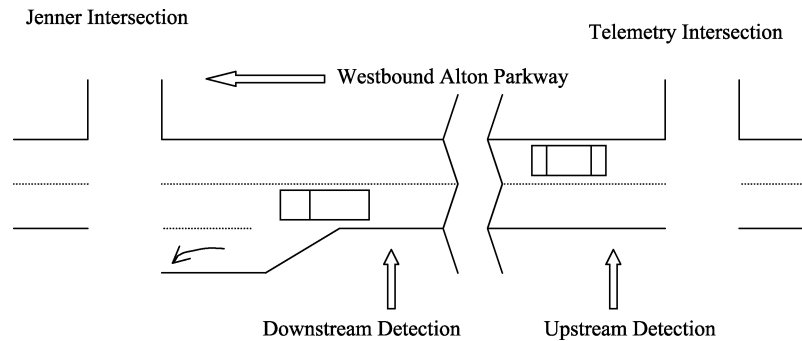


Fig. 2. Data collection site in Alton Parkway, CA.

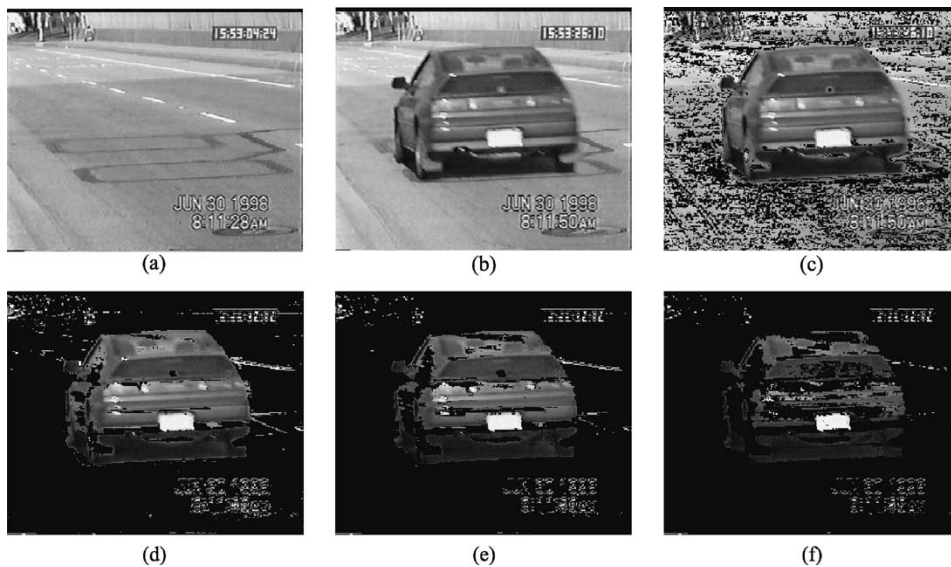


Fig. 3. Background subtraction and image thresholding: (a) background; (b) vehicle image; (c) threshold = 20; (d) threshold = 60; (e) threshold = 80; and (f) threshold = 100.

stations bounding a two-lane section of Alton Parkway within the intersections of Telemetry and Jenner Streets. Each detector station had double inductive loops in a speed trap configuration. The distance between the two detector stations was 130 m (425 ft). The inductive loops were standard 1.83 m \times 1.83 m (6 ft by 6 ft) rectangular loops that were commonly used by many transportation agencies. The original goal of this data collection was to detect vehicles using inductive loop detectors and video footage of the traffic was recorded for ground truth purposes only. Therefore, video detection issues such as lighting, angles, and centering the frame of vision were not considered a priority.

A complete ground truthing of the data was performed in order to validate the results obtained from the automated reidentification system. Every vehicle image from the downstream point was manually matched with the corresponding upstream image and a unique identification number was assigned to each vehicle. It took several research assistants several weeks to perform this ground truthing; however, this was necessary in order to validate algorithm results.

The data was collected during the morning peak between approximately 8:00 AM and 9:30 AM at the downstream station. This data set contained 581 vehicle signature pairs, or 1162 vehicles. The first 200 vehicle pairs were used for training. The

average flow over that time period was 612 vehicles/h for two lanes. Due to arterial signalization and varying traffic demand, different speeds, acceleration profiles, and traffic flow levels were observed during the 1.5-h period. The maximum observed speed was 30.66 m/s (68.68 m/h). The minimum speed was 5.47 m/s (12.25 m/h). The arithmetic mean speed was 20.77 m/s (46.52 m/h). The standard deviation of the speed was 4.11 m/s. The longest electronic length (length of detector and vehicle) observed was 20.31 m. The shortest electronic length observed was 3.89 m. The mean electronic length was 4.83 m.

The video-collection setup consists of four video cameras recording two lanes of traffic in each of the upstream and downstream locations. From this continuous video footage, one can visually identify many of the vehicles by type and color. The first step in the data-reduction process is to capture the video data into the computer. A video-capturing board is used to digitize the video footage into still images stored in jpeg format (ISO 10918-1). The processing algorithm reads each of the still image files and stores the image as a variable of "C++" image class. This image class contains the RGB values of the vehicle image and other information, such as the vehicle record number, lane, and time of arrival. The vehicle record number is a unique identification number used to match the video image to the inductive signatures. The RGB color space is used because of its

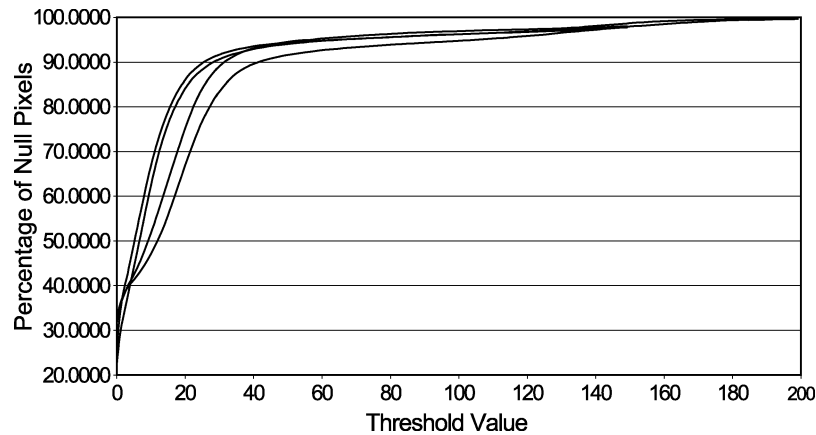


Fig. 4. Adjustment of threshold.

simplicity in representing images. The image class is created with the ability to manipulate the RGB values of each pixel in an image. Each pixel has RGB values ranging from 0 to 255 (8 b).

Processing the vehicle images involves five main steps; namely, contrast stretching, background subtraction, quantization, normalization, and obtaining the color feature vector *c*. The distribution of light and dark pixels is the contrast of an image. Ideally, an image containing a wide distribution of intensities utilizes the full dynamic range. However, if an image is either too light or too dark, some intensities are not utilized and are wasted. During the acquisition of vehicle images, contrast stretching was applied to enhance images.

Subtraction is the process of determining the differences between two images. If one image contains a background of the roadway without any vehicles and the other image contains a vehicle, then the background subtraction will produce the image of the vehicle without the surrounding roadway. Fig. 3 shows the background image in (a), the original image of the vehicle in (b), and various subtracted images in (c)–(f). The time stamp on the upper right-hand corner of the images is automatically set to null and is not used by the reidentification algorithm.

In order to determine the optimum threshold value for background subtraction, threshold curves and graphical images are used together. After the reidentification algorithm is developed, the threshold value is reoptimized using training data and the new optimum value is explained in the results section. The initial threshold curves are formed by varying the threshold value and noting the percentage of null pixels that results from background subtraction. Fig. 3 shows various background subtracted images for different thresholds and Fig. 4 shows the results of comparing the percentage of blacked out pixels with the comparison thresholds for various vehicles. Under threshold values of 30, a great portion of the image that is not part of the vehicle is present. Around values of about 60, the shape of the vehicle is the most pronounced, as most of the background has been removed. Finally, values around 80 or higher are best for identifying colors present in the vehicle. Fig. 4 shows that after reaching a threshold value of around 40, the rate at which the percentage of pixels becomes null is reduced significantly.

The next step is to perform quantization of the background image. The use of true color information yields 256^3 or 16.8 mil-

TABLE I
SAMPLE VEHICLE COLOR INFORMATION

RGB Number	Count	Color
255 255 255	23	Black
254 254 254	14	Black
253 253 253	8	Black
167 164 255	7	Blue
115 112 219	7	Blue
113 111 218	6	Blue
253 253 255	6	Black
159 169 255	5	Blue
166 177 255	5	Blue
147 126 255	5	Blue
106 098 219	5	Blue

lion RGB values (colors). However, each distinct RGB value appears in only a few pixels. For example, Table I is the top portion of a chart of the RGB values and corresponding colors present in an image. In this particular case, there are only 4600 distinct RGB values present in the 5400 pixels that are not blacked out. The RGB values present mostly correspond to a shade of the vehicle color in question. The fact that there are so many RGB values pertaining to the same color in the image makes the process of reidentification difficult.

Instead of using every shade of color in the RGB three-dimensional cube, the RGB values are quantized or grouped into subsets as discussed in the feature extraction section. Fig. 5(a) shows the RGB space of all 16.8 million RGB values and Fig. 5(b) shows the same space quantized into eight different cubes, each specifying an overall color that includes different shades.

Histogram decomposition is a method commonly used for processing images. The goal is to reduce the size of the color vector by eliminating the colors that occur less frequently. However, after investigating this method and its effects on reidentification, it was found that the full color vector of dimension 125 yielded better results.

VI. RESULTS

In this section, the results of training the image-processing parameters, training the reidentification algorithm, and testing the algorithm will be presented. All training results are obtained by using the training set of 400 vehicle signatures. The testing

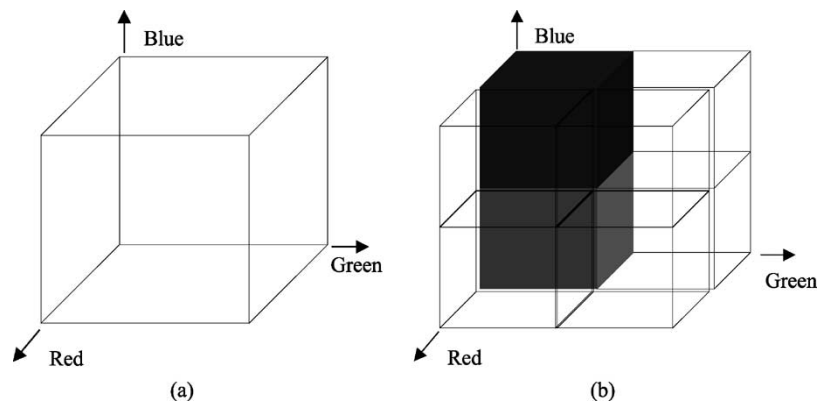


Fig. 5. Graphical illustration of the quantization process. (a) RGB space and (b) quantized RGB space.

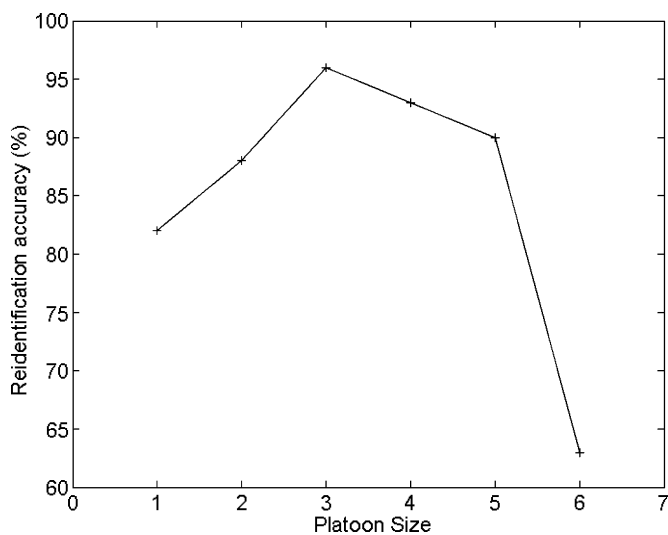


Fig. 6. Reidentification accuracy versus platoon size.

results are obtained using the remaining 381 vehicle pairs (or 762 vehicle signatures) that are not part of the training set. Concerning the image-processing parameters, sensitivity analysis is performed on the background subtraction threshold and the color quantization level. First, the optimum number of vehicles in a platoon is determined by varying the platoon size from one to six and observing what platoon size maximizes the reidentification accuracy. This is done using linear fusion of three features, namely, the vehicle signature vector, the vehicle velocity, and the platoon traversal time. The reidentification accuracy is found using the training data only. The fusion weights are determined using an exhaustive search such that the reidentification accuracy is maximized. As shown in Fig. 6, the best platoon size consists of three vehicles.

Fig. 7 shows the results of reoptimizing the threshold value for background subtraction based on reidentification results using the training data only. Also, the reidentification accuracy is computed using only the color feature vector. Fig. 7 shows that threshold values from 70 to 85 will give the best reidentification performance. Visual inspections of the individual images were helpful in confirming the numerical results obtained by using the ground truth data set. Low threshold values allow some of the background image to leak into the picture, while high threshold values eliminate portions of the vehicle image.

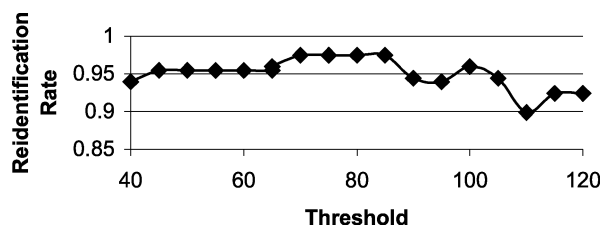


Fig. 7. Sensitivity analysis of image threshold.

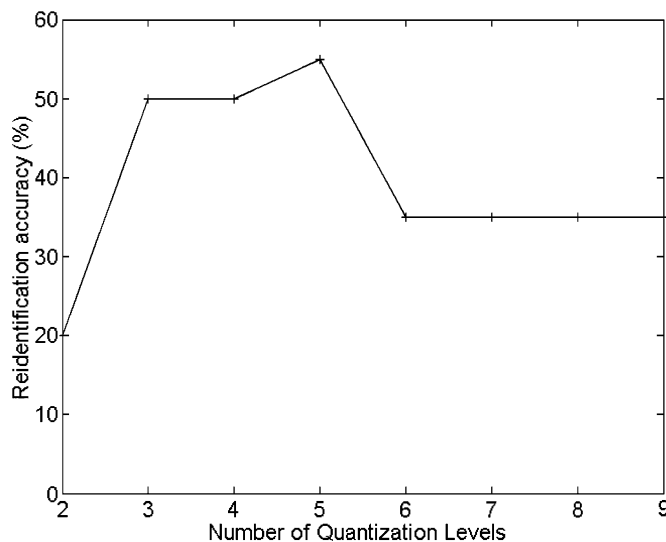


Fig. 8. Effect of quantization level on reidentification accuracy.

An investigation into the sensitivity of the reidentification algorithm to changes in quantization level (again using the color feature and the training data only) is made and the results are shown in Fig. 8. This figure shows that a quantization level of 5 is the optimum value for the reidentification of the training set. Quantization levels of up to 30 are tested and not shown because the storage requirements become significant with no improvement in performance.

Table II gives the results of the multidetector fusion algorithm using linear fusion. As was previously mentioned, the fusion weights are determined by searching an n -dimensional grid of real numbers and finding the optimum combination that gives the best performance on the training data alone. This optimum weight combination is used for the test data. The results

TABLE II
VEHICLE REIDENTIFICATION ACCURACY FOR FEATURES AND FUSION COMBINATIONS

Vehicle Signature Fusion Weight w_s	Velocity Fusion Weight w_v	Color Fusion Weight w_c	Platoon Traversal Time Fusion Weight w_p	Vehicle Reidentification Accuracy (%)
1	0	0	0	86.87
0	1	0	0	54.92
0	0	1	0	75.82
0	0	0	1	74.78
0.6	0.4	0	0	87.39
0.005	0	0.995	0	89.29
0.022	0	0	0.978	88.08
0	0.013	0.987	0	76.51
0	0.37	0	0.63	72.71
0	0	0.985	0.015	82.21
0.005	0.025	0.97	0	90.50
0.015	0.425	0	0.56	89.12
0.01	0	0.71	0.28	90.50
0	0.015	0.98	0.005	79.45
0.005	0.015	0.955	0.025	91.36

in Table II show fusion weights for four features instead of the six that we describe, because the weights pertaining to the maximum inductive amplitude feature and the electronic length feature had values of zero on the training set we used. These two features are kept in the general formulation in Section IV, because based on previous experience they could contribute significantly if another data set were used (see [4]).

Table II shows several valuable results. First, the last row shows the best overall vehicle reidentification accuracy of 91.36% for the test data. The corresponding training set accuracy is 97.5%. This result shows that there is potential in using the multidetector fusion algorithm for deriving traffic parameters that require high reidentification accuracy or a large reidentification sample. For example, the tracking of traffic patterns (origin/destination demands) requires a high reidentification accuracy and the analysis of travel time reliability with the use of travel time distributions requires a large reidentification sample. Second, Table II shows how the multidetector fusion system produces better results than single detector system. Row 3 shows an accuracy of 75.82% when only the color information is used for reidentification. Row 5 shows an accuracy of 87.39% when only the inductive signature information of vehicle signature and velocity are used. It is important to note that the even though the fusion

weights add to one, the magnitude of the fractional weights of different features cannot be compared directly with each other, since features use different units of measure.

Even though the improvement in accuracy of the multidetector over the single detector was not very large, it is important to remember that the advantages of multidetector fusion include reliability and robustness in addition to increased accuracy. Table II shows the feature weight for color is 0.955 for the best multidetector case, which points to the fact that the incremental gain in accuracy of 4% was not just due to a small addition of the color feature, but a significant contribution of the color or video feature. This fact shows that there is significant redundancy in the system and, hence, robustness since both 0 and 0.955 feature weight contribution from the color feature can produce around 90% accuracy.

VII. SUMMARY AND CONCLUSION

The results of an initial investigation into the use of multidetector fusion for vehicle reidentification show that fusion yields better results than the use of a single detector. The results are especially promising because the video image used for this investigation is not optimized for the purpose of color extraction. The vehicle images are rear views of vehicles, while side or top

views seem to be intuitively better for color extraction. Also, the multiple cameras used in data collection are not calibrated to each other. Neither the angle of vision nor the lighting condition is kept the same from one site to the other. It is highly likely that video images of better quality can improve the results of vehicle reidentification.

This initial investigation into fusing color information uses the RGB color space. However, it is worthwhile to investigate other representations of color space such as HSI or YC_bC_r . HSI represents color using hue, saturation, and intensity and YC_bC_r separates chrominance from luminance. These other representations might be more robust and less sensitive to changes in lighting or other field conditions. Also, transformations of the color information into other bases might highlight features that will improve reidentification or compress data, or do both.

Vehicle reidentification is valuable in deriving section measures of traffic performance such as travel time, travel time variability, density, and dynamic origin/destination demands. Vehicle reidentification is especially useful on sections of arterials, because of the element of signal timing. It is difficult to compute arterial travel times accurately using point measures, since lost times associated with starting up and stopping are not measured directly. Therefore, more accurate travel times have the potential for improving arterial performance assessment and adaptive signal timing. It would be even better if the vehicle reidentification system could be tied into the signal control system. This tie-in will improve the accuracy and possibly yield real-time estimates of startup delays and saturation flow rates.

There are various tradeoffs associated with the implementation of this system on arterials as opposed to freeways. In general, there tends to be more "turn over" in traffic on arterials than on freeways. This will require detection on every important segment if a large sample is desired. A large sample is desirable if travel time variability and travel time distributions are important, whereas a smaller sample is adequate for measuring average conditions. The hardware configuration that was used in this paper is not the most common configuration of using only approach detection. There are adaptive control systems that use a similar departure configuration, but they are less common. Because the traffic on freeways tend to travel for longer distances and are not disrupted by signalization, wider spacing can be used in the freeway case. However, because of the wider spacing, the platoon feature will be less important with increasing distances. Table II shows an accuracy of around 90% in the test data without the use of the platoon traversal time feature.

Video images were chosen based on convenience. However, there are many other detectors that might be suitable for use in vehicle reidentification. Some of these detectors output similar information, while others output information that are uncorrelated with each other. In either case, the use of multidetector fusion can possibly improve the accuracy and robustness of vehicle reidentification systems. As the cost of detectors and computation become increasingly more affordable, the deployment of such multidetector systems becomes possible.

This investigation used a limited data set obtained from one section of roadway during a particular time of the day. However, over a longer period of time and over different types of roadways

many other conditions could affect the performance of the reidentification system. This includes issues dealing with lighting, weather conditions, day transitions, traffic volumes, traffic behavior, etc. The authors hope to investigate other field conditions in the future. The feasibility of multidetector fusion for vehicle reidentification has been demonstrated, especially with the use of color information and inductive signature.

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