the Golden Gate Bridge and use the previous equation to calculate a capacity increase of ICAP = 18 percent for the $1.00 toll by using TM = 2.7 s and assuming that the booths are not buffered. When the booths are buffered, ICAP = 34 percent.

The result is consistent with a test of tandem tolls conducted at the Golden Gate Bridge in 1969. By using a makeshift arrangement where the second toll collector stood out in front of the islands, the flow rate was increased from 625 to 725 vehicles/h (16 percent) (2, p. 364).

Tandem tolls could also be used in a truck toll lane. Cycle component times for a tractor-trailer truck are TC = 14 s and TM = 7.5 s (8, p. 189).

The tandem move-up in time can be estimated as TM = 5.0 s.

The effectiveness of tandem tolls increases as the toll-collection cycle time increases. The previous equations were applied to derive Table 2.

APPLICATION TO REDUCE NEED FOR PLAZA WIDENING

I have presented an example that illustrates one of the situations in which a tandem toll system would be more economical than additional conventional toll lanes for increasing a toll plaza's capacity on weekends (3).

The cost parameters in the example are as follows:

1. Capital cost per additional booth:

Item	Cost ($000s)
Toll booth	40
Toll registry equipment	30
Tapered approach road (1500 ft)	1500
	1640

2. Present worth of staffing: half-day/week, $60 000.

By using these parameters, the capacity increase per unit of cost is

1. Tandem: 1.6 cars/(h·$1000) and
2. Conventional: 0.6 car/(h·$1000).

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Reliability of Classified Traffic Count Data

PETER DAVIES AND DAVID R. SALTER

The reliability of classified traffic count data collected for the planning and operation of highway systems is examined. Manual classified count data are subject to serious errors, whereas automatic vehicle classification with modern microprocessor technology may have other accuracy problems. Accuracy checks carried out in the United Kingdom are described for two automatic classification systems—for simple classification by using inductive loops alone and for detailed classification by using loops and axle detectors in combination. An evaluation of automatic classification equipment, including these simple and detailed systems, has been carried out in the United States by the Maine Department of Transportation. The results of these studies are described. The accuracy of simple vehicle classification based on vehicle length alone is limited by the fundamental properties of inductive-loop sensors. However, at sites with good lane discipline, the accuracy of classification is likely to be sufficient for most routine purposes such as the measurement of passenger-car-equivalent flows. Tests in the United States have shown that the reduced reliability of pneumatic-tube sensors leads to poor classification accuracy when these sensors alone are used for vehicle detection. More detailed vehicle classification methods can give greater accuracy, in excess of 90 percent, but as traffic conditions deteriorate, accuracies reduce. In the detailed classification method, there are difficulties in discriminating between certain cars, vans, and trucks, particularly where lane discipline is poor. Further developments of automatic classification techniques are currently in progress, and improvements are anticipated under urban traffic conditions and in the portability of detailed classification equipment. However, simple classified counters are already available and already have a part to play in displacing unreliable manual counts. Future trends in labor and microprocessor costs are anticipated to be such that as new developments become available, their rapid exploitation will become increasingly attractive.

Classified traffic counts have been carried out for decades to provide basic information used in the design, maintenance, and management of highway systems. In the past, manual counts have been the only source of classified flow data; automatic counts have been limited to the recording of axle pairs or total numbers of vehicles. More recently, the microprocessor revolution has changed this state of affairs, so that automatic vehicle classification and monitoring is now a practical proposition in many situations.

The demands for classified traffic count data are various. Simple classification into some five or six broad categories of vehicle is a common requirement for highway design or traffic signal-timing procedures based on passenger-car equivalents (PCEs). Longer-term monitoring of classified traffic flows provides the basis for forecasts of future traffic, disaggregated by type of vehicle. The economic appraisal of highway schemes may also require a knowledge of the mix of vehicle classes and their characteristically different operating costs, occupancies, and values of time.

A more detailed vehicle classification could also have a part to play in some areas of growing concern. Axle-weight distributions of different types of truck can be monitored at weighbridge sites and the data applied to pavement design or maintenance at other locations through detailed classified counts. The allocation of road damage costs to different classes of vehicle on toll highways or via general vehicle taxation again requires the detailed classification of freight vehicles. Other forms of classification, such as speed category, headway, and lane or turning movement, may also play important roles in special situations.

Relatively little is known about the sensitivity of design procedures or traffic control measures to errors in the classified count data. One study does suggest that highway scheme cost-benefit appraisal can be highly sensitive to the mix of vehicle classes assumed (1). Traffic forecasting could also be very sensitive, based as it is on the extrapolation of past trends from an assumed current situation; any errors in the base data may well be magnified in forecasts of the future. Finally, pavement design, with its high-order power-law relationship between axle weight and road damage, could eventually prove to be most sensitive of all to the basic traffic data input.

In this paper, we consider the reliability of classified traffic count data produced by manual and automatic means. Recent work on the accuracy of manual classified counts suggests that even for closely supervised, well-conducted surveys, results are much less reliable than might commonly be supposed. Automatic classification offers opportunities to overcome some accuracy problems but instead can lead to errors of a different nature than those resulting from manual enumeration.

We begin by reviewing available evidence on the reliability of manual classified traffic counts. Next, two automatic classification systems, for which results are presented in a number of accuracy studies, are described. Road-sensor design and software are two key areas in automatic classification, so the scope for their improvement is considered. Finally, the relative merits of automatic and manual classification are assessed in the context of the current state of the art.

MANUAL CLASSIFIED TRAFFIC COUNTS

At first sight, manual classified traffic counting appears a straightforward task. Passing vehicles are recorded for predetermined time periods either by marking different sections of survey forms or by hand-operated counters in order to build up a picture of the traffic flow disaggregated by vehicle class. In practice, however, this simple procedure gives rise to considerable scope for error. Vehicles can be missed, double counted, wrongly identified, or entered in the wrong place. There are many reasons why these mistakes occur. For example, enumerators are locally recruited temporary staff whose motivation and skill may vary considerably. Counting can be a tedious process; it requires extended concentration, which may easily be broken. The importance of the data may be far from obvious to temporary staff, so the apparently harmless invention of results may prove a strong temptation. Close supervision or performance checks are difficult and time-consuming, so sanctions against carelessness are rare and rewards for vigilance are generally nonexistent.

Even where counts are properly conducted and well supervised, there is evidence to suggest that results can be unreliable. The U.K. Department of Transport compared simultaneous counts by a dedicated full-time team with those of teams locally recruited for routine census work at three sites (2). Although no consistent biases emerged, there were considerable variations in both absolute totals and percentage of discrepancies. It was concluded that errors were apparently serious, both in absolute and percentage terms.

Further comparisons are described in an internal note of the U.K. Department of Transport, the results of which are summarized elsewhere (3). The results suggest that 95 percent confidence limits on 16-h total flows are probably within ±10 percent but that considerably greater intervals apply to most individual vehicle classes:

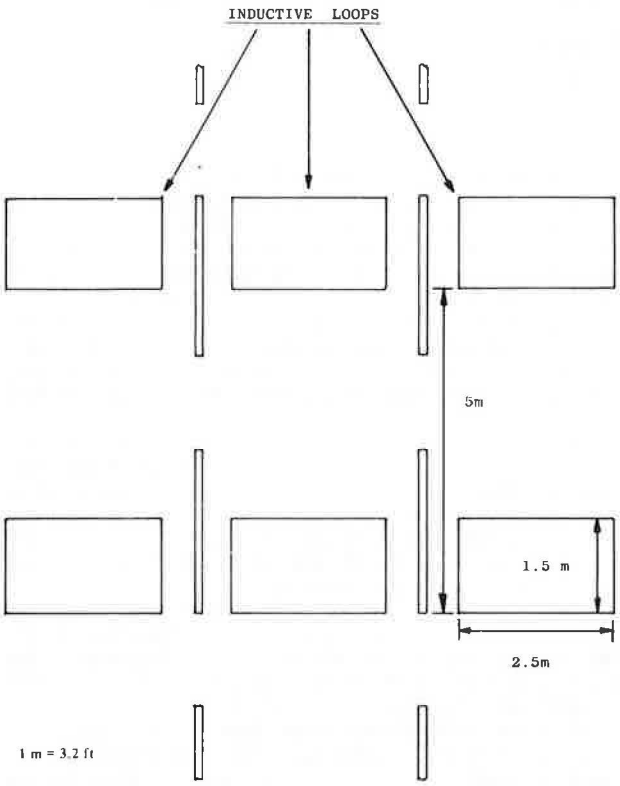
Vehicle Class	95 Percent Confidence Limit (%)
Two-wheeled motor vehicles	±35
Cars and taxis	±10
Buses	±37
Light trucks	±24
Other trucks	±28

There was some evidence of difficulty in distinguishing "light" from "other" trucks, despite special markings carried by U.K. trucks; the interval fell to ±18 percent for all freight vehicles combined. However, the greatest percentage of errors is seen in two distinctive categories--motorcycles and buses.

In view of these major discrepancies in 16-h counts, how good will peak-period data prove to be? The answer must be almost certainly that they will be worse, since there is less scope for compensating errors within shorter-duration counts. Moreover, at peak periods, enumerators will be fully stretched, and more vehicles may be missed or guessed. Our test with simultaneous film recording of traffic flows shows that even highly motivated research observers find it impossible to count with high accuracy and are often unaware that they have made mistakes. In less-controlled surroundings the problems are likely to be still more severe.

The quality of manual classified traffic counts can clearly give cause for concern. When coupled with the errors of sampling, scaling, and forecasting, the errors of manual enumeration may well be sufficient to produce suboptimal design or management decisions based on wrong information. Whether anything can be done about this at reasonable cost, for example, through the greater use of microprocessor-based automatic vehicle classification, is another question. This question is considered in the remainder of this paper.

Figure 1. Typical sensor configuration for simple classification.



SIMPLE AUTOMATIC CLASSIFICATION

For many routine purposes such as the determination of PCE traffic flows, simple classification into a small number of vehicle categories may well be sufficient. One type of automatic vehicle classifier already available counts vehicles into separate bins according to their overall lengths. Tests are described on the accuracy of such a system, a 12-bin speed or 4-bin length classifier manufactured by the Golden River Corporation.

When configured as a length classifier, this portable microprocessor-based system records classified traffic flows disaggregated into length categories specified by the user. The system's main component consists of a roadside processing unit sealed with its rechargeable battery pack into a cast aluminum case and linked to inductive-loop sensors in the road. A complementary retriever unit is connected to the roadside processor for the initial configuration of the system and for the recovery of data at intervals as required.

The road sensors consist of up to three pairs of matched inductive loops; each pair of loops is located in a single traffic lane (Figure 1). A wide range of loop dimensions will be accepted by the equipment, but typical loops would be 1.5 m long by 2.5 m wide (4 ft 11 in by 8 ft 2 in) spaced 5 m (16 ft 5 in) apart. The loops can either be cut into permanent slots or be attached temporarily to the road surface.

The classifier operates by timing vehicles between the two loops to give individual vehicle speeds. These data on speed and on the vehicle's presence time over each loop allow vehicle lengths to be calculated. Each vehicle is logged into one of four counting bins according to its estimated length. By the selection of appropriate length bands, simple vehicle classification is practicable into categories of motorcycles, cars, small trucks, and heavy vehicles. Total flows in each class are recorded in memory at intervals of between 1 min and 24 h as preset by the user.

One optional output for use in setting up the system consists of individual vehicle speeds or lengths, which appear on the liquid crystal display on the front panel of the retriever unit. This facility was used in tests on the accuracy of the system for individual speed or length comparisons. Independent speed checks were carried out by precise timing of vehicle leading axles between pairs of pneumatic tubes, located next to the inductive loops of the speed and length classifier. Classifier length measurements were compared with vehicle manufacturers' data following manual identification of vehicle makes. The accuracy of the independent measurements has been assessed elsewhere (4).

Precise timing was carried out by using a portable roadside microcomputer. A machine code routine was written for a Golden River Environmental Computer to scan the sensors and increment a 32-bit counter between signals on successive tubes. The routine was calibrated by using a stopwatch over intervals of 30 min to 1 h, which gave a count rate of 23 485/s. Repeated short-duration checks against a microsecond-resolution advance timer showed no statistically significant systematic error and a random standard error of ±0.11 ms (±0.02 percent).

Hand-written recording of vehicle speeds, lengths, or makes was only possible at low flows. In other cases, individual vehicle results were dictated into a portable tape recorder or where possible were recorded automatically in the portable roadside computer memory. At the busiest site, immediate identification of vehicle makes was impractical, so a cinecamera was triggered by a road sensor to provide a photographic record of each vehicle. Vehicle makes were subsequently identified from the film.

The three sites selected for accuracy checks of the speed and length classifier were each of distinctive character. The first was a 6-m (20-ft) two-way internal-access road on the University of Nottingham campus, which provided a low-speed, low-volume site at which private cars predominate. The second site was an urban dual two-lane highway with a 65-km/h (40-mph) speed limit that carried fairly high volumes of general mixed traffic and buses. The final site was a rural high-speed single-lane highway with local dualing at intersections. Its modest traffic volumes included a higher proportion of commercial vehicles than those of the other sites.

SIMPLE CLASSIFICATION ACCURACY RESULTS

The results of individual vehicle speed comparisons are summarized below (1 km/h = 0.6 mph):

Site	No. of Vehicles	Mean Speed (km/h)	Systematic Difference (km/h)	Random Difference (km/h)
Low speed (1)	204	32.82	-0.32±0.08	±1.10
Low speed (2)	215	31.29	-0.49±0.06	±0.86
Urban	327	61.65	-0.09±0.05	±0.87
High	161	71.54	-0.99±0.09	±1.07

Speed measurement forms the first stage of length classification, so its accuracy is of considerable interest. The two sets of results presented for the low-speed site correspond to measurements on different days.

At the low-speed and the high-speed sites there were significant systematic differences between the speed measurements of the classifier and the independent system. A proportion of the differences may be due to systematic error in the independent speed measurements. Another factor, however, could be the matching of loop pairs for speed measurement; precise geometry and equality of loop feeder lengths appear to be of considerable importance. Systematic errors could if necessary be overcome by individual site calibration.

The random discrepancies in speed measurements do not vary greatly between sites. A proportion of the discrepancies is simply due to rounding to the nearest kilometer per hour on the liquid crystal display, which of itself would account for about ±0.3 km/h. A smaller proportion will be due to errors in the independent speed measurements. The remaining random error in the speed measurements is unlikely to be of importance in vehicle classification.

The results of the individual vehicle length comparisons are given below (1 m = 3.2 ft):

Site	No. of Vehicles	Systematic Difference (m)	Random Difference (m)
Low speed	91	-0.70±0.06	±0.54
Urban	276	-0.90±0.04	±0.68
High speed	105	-0.17±0.06	±0.64

Lengths are systematically underestimated at all sites, apparently due to the use of two-turn loops instead of the three turns normally recommended by the manufacturer. The variations between sites are probably associated with different feeder lengths and indicate a need for individual site calibration.

Random errors are also significant; they are of a similar order of magnitude at each site. The main contributor to random error appears to be differences in the lateral position of vehicles. The tabulation below shows how vehicles passing over either edge of the loop have their lengths systematically underestimated in relation to those near the center. At this site the loop width was 2 m (6 ft 7 in) (1 m = 3.2 ft):

Distance from Curb to Nearside Wheel (m)	No. of Vehicles	Systematic Difference (m)
0.0-0.9	12	-1.36
0.9-1.2	22	-1.02
1.2-1.4	60	-0.74
1.4-1.6	58	-0.67
1.6-1.8	68	-0.89
1.8-2.1	43	-0.96
>2.1	5	-1.24

These results provided a strong indication that the variations in length measurement were associated principally with the characteristics of inductive loops rather than those of the measuring equipment. The effective length of loops appears to vary considerably with the lateral position of vehicles as well as with feeder lengths and number of turns. With this in mind, some laboratory and field trials were carried out at the University of Nottingham into the fundamental properties of inductive-loop layouts.

The laboratory tests set out to examine the magnetic fields of loops by breaking them down into three component parts at right angles. Experimental techniques have been described in detail elsewhere (5). The experiments aimed to produce contour maps that show the limits of the zone of detection for each component of the loop's magnetic field.

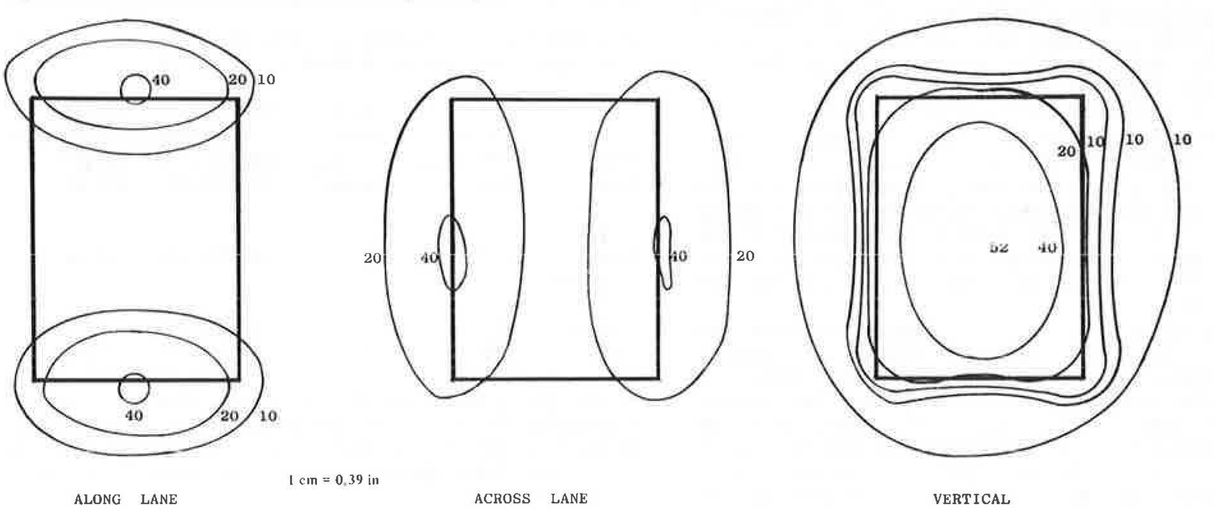
Typical contour plots for a three-turn rectangular loop are shown in Figure 2; the heights of the zone of detection are shown in centimeters. The loop was a one-third scale model of a 2.8-by-2.0-m configuration (9 ft 2 in by 6 ft 7 in).

For a two-dimensional body such as a thin steel plate, detection results when the component of the magnetic field cuts it at right angles. Thus detection begins when a vehicle's front panel enters the horizontal field running along the traffic lane. It ends as the rear panel leaves the equivalent downstream field. Vehicles crossing the edge of the loop can be picked up as their side panels cut the horizontal field running across the traffic lane. The curvature of these field boundaries is such that the loop's effective length changes continuously across its width. These findings were confirmed in a number of field trials.

Experiments with a wide variety of loop layouts indicated that although this basic problem cannot be wholly overcome, it can be reduced by the adoption of broader loops of rectangular outline. The overall width must be limited, however, by the need to prevent the zones of detection from spreading too far into adjacent lanes.

These basic limitations of the loop sensor con-

Figure 2. Zones of detection for three-turn rectangular loop.



strain the accuracy of simple vehicle classification by using loops alone. The effect of the errors will, however, depend on the vehicle length categories selected in relation to the distribution of lengths within the traffic stream. Misclassification will only affect vehicles whose lengths are similar to the category boundary values, and even here random errors will tend to cancel out. Classification accuracy will also be heavily dependent on lane discipline at the survey point, which varies considerably from site to site. Preliminary results from U.K. sites suggest that simple classification can be reasonably reliable based on vehicle length from loops alone.

One weakness of length classification is its inability to distinguish buses from long freight vehicles. An additional parameter, chassis height, can be estimated from the strength of the loop signal, providing opportunities for the extension of simple classification to this additional vehicle category. The problems of chassis height measurement are discussed in later sections.

DETAILED AUTOMATIC CLASSIFICATION

In cases where more detailed information is needed or where more accurate results are sought, a more complex form of automatic vehicle classification may be necessary. The accuracy tests described in this paper were carried out on a detailed classification system that was developed by the U.K. Transport and Road Research Laboratory (TRRL). It consists of permanent sensors in the road for vehicle detection and a roadside, mains-powered microprocessor system for the calculation of various parameters permitting detailed vehicle classification.

The road sensors consist of one inductive loop and two triboelectric axle sensors per lane, as shown in Figure 3. Sensor dimensions can be varied (these are specified as initial data to the microprocessor system), although standard layouts have been used at most classification sites to date. The axle-detector spacing is usually 1 m (3 ft 3 in), and loops are typically 2.8 m long by 2.0 m wide (9 ft 2 in by 6 ft 7 in).

The roadside equipment includes loop-detector electronics and axle-detector signal-processing units, as well as the microprocessor and its peripherals. These initial interfaces transform raw pulses from the sensors into square-wave signals suitable for input to the microprocessor. The microprocessor itself is an RCA 1802 COSMAC single-board machine with 15K EPROM holding the classification software and 2K RAM for temporary data storage. Permanent recording is on magnetic cartridge. The system is shown in Figure 3.

The classification system resolves road sensor signals to 1-ms timing for the calculation of vehicle parameters. The first parameter, vehicle speed, is calculated from the times of the leading axle on successive axle detectors. Given the speed, wheelbase lengths are derived from the time intervals between axles on a single-axle detector. Overall length is estimated from the vehicle's presence time over the inductive loop. Finally, chassis height is estimated from the strength of the inductive loop signal to assist discrimination between certain classes of vehicle with similar wheelbase and overall lengths. The detector signals from a typical vehicle are shown in Figure 4.

The microprocessor compares the vehicle parameters of wheelbase, overhang, and chassis height with limiting values held in memory. When a parameter match is found, the vehicle class is identified. Twenty-five separate categories of vehicle are distinguished by the existing system, which allows considerable flexibility in modes of aggregation to suit the requirements of individual users. The vehicle categories are shown in Figure 5.

Output from the system is available in real time as a vehicle-by-vehicle listing. More commonly, summaries are produced and stored on magnetic cartridge at intervals specified by the user. The system is capable of producing data on vehicle flow, time headway, speed, class, wheelbase, and overall

Figure 3. Sensor configuration and roadside equipment for detailed classification.

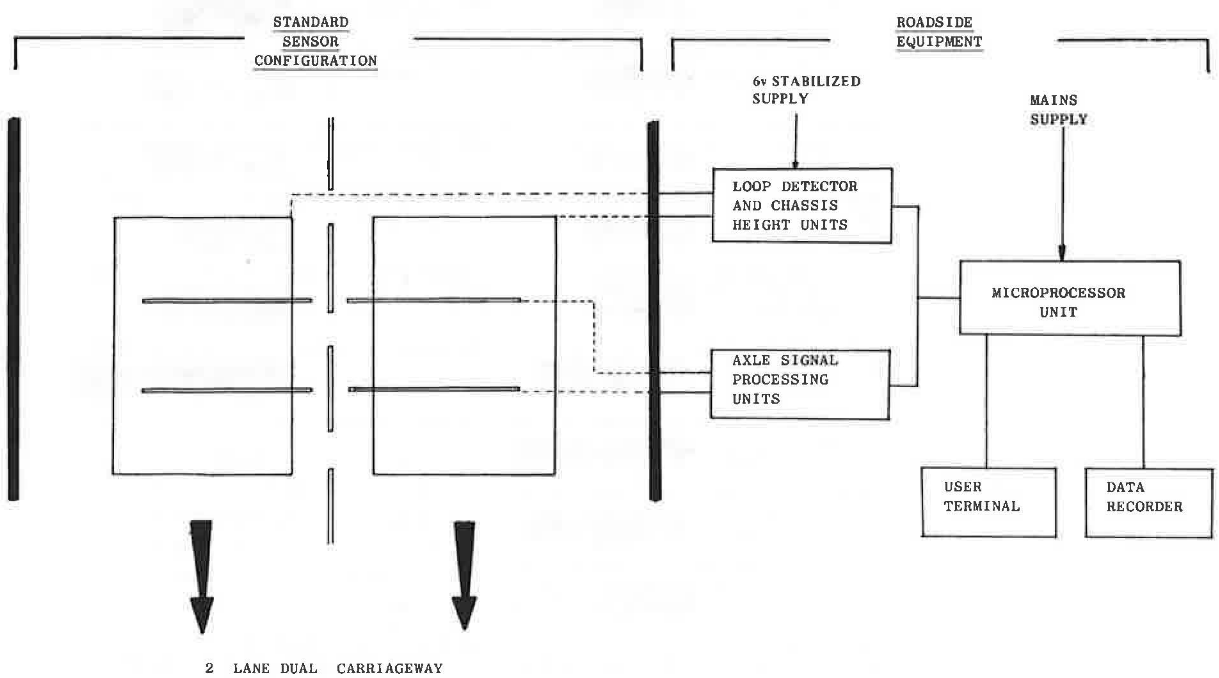


Figure 4. Sensor time sequence diagram.

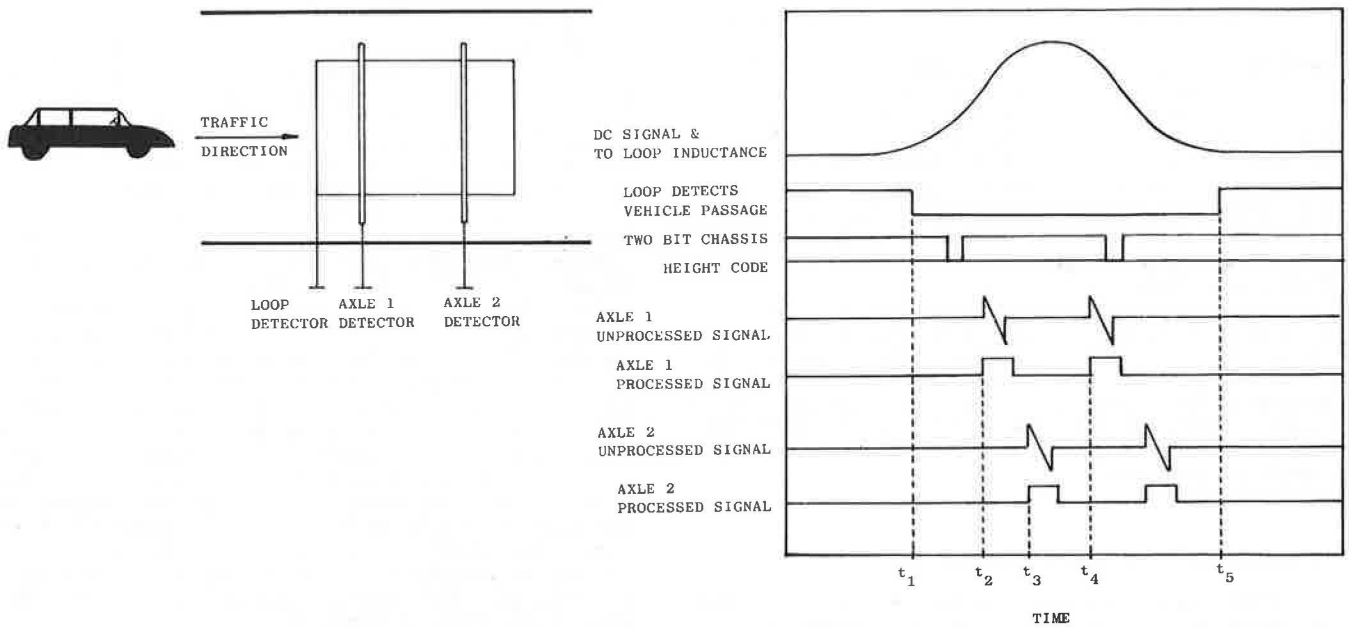


Figure 5. Vehicle categories for detailed automatic classification.

Class no	Vehicle description	Class no	Vehicle description
0	Moped, scooter motorcycle	45	Rigid 2 axle HGV +1 axle caravan or trailer
1	Car, light van, taxi	46	Rigid 2 axle HGV +2 axle (close coupled) trailer
2	Light goods vehicle	51	Artic, 2 axle tractor +1 axle semi-trailer
21	Car or light goods vehicle+1 axle caravan or trailer	52	Artic, 2 axle tractor +2 axle semi-trailer
22	Car or light goods vehicle+2 axle caravan or trailer	53	Artic, 3 axle tractor +1 axle semi-trailer
31	Rigid 2 axle heavy goods vehicle	54	Artic, 3 axle tractor +2 axle semi-trailer
32	Rigid 3 axle heavy goods vehicle	55	Artic, 2 axle tractor +3 axle semi-trailer
33	Rigid 4 axle heavy goods vehicle	56	Artic, 3 axle tractor +3 axle semi-trailer
34	Rigid 3 axle heavy goods vehicle	61	Bus or coach, 2 axle
35	Rigid 4 axle heavy goods vehicle	62	Bus or coach, 3 axle
41	Rigid 2 axle HGV +2 axle drawbar trailer	7	Vehicle with 7 or more axles
42	Rigid 2 axle HGV +3 axle drawbar trailer	1N	Vehicle with 1 axle counted
		2N	2 axle vehicle not otherwise classified
43	Rigid 3 axle HGV +2 axle drawbar trailer	3N	3 axle vehicle not otherwise classified
		4N	4 axle vehicle not otherwise classified
44	Rigid 3 axle HGV +3 axle drawbar trailer	5N	5 axle vehicle not otherwise classified
		6N	6 axle vehicle not otherwise classified

TRRL VEHICLE CLASS LISTING COMPATIBLE WITH EEC REGULATION R1108/70 length for four lanes of traffic with capacity flow in each lane.

As an example of the classification methodology, consider the problem of correctly classifying the following three types of four-axle vehicle:

1. Class 22, car + two-axle trailer;
2. Class 46, rigid two-axle truck + two-axle (closed-coupled) trailer; and
3. Class 52, two-axle tractor + two-axle semi-trailer.

The classification program contains the vehicle dimension reference table, which for these three categories consists of the values given in Table 1.

From Table 1 it can be seen that the class-46 vehicle can be identified without using the chassis height code. Separation of classes 46 and 52 occurs on the second wheelbase dimension, and similarly classes 46 and 22 are separated by the first wheelbase. The separation between classes 22 and 52, however, is based on the chassis height code if and only if the wheelbase or wheelbases actually overlap.

Similar data are held in memory for other categories of vehicle; limiting values for the appropriate parameters are specified. Should the software fail to find a match to any of the 25 recognized classes, the vehicle is logged according to its number of axles but is otherwise unclassified. Further details of the system and its operation are given elsewhere (6,7).

Table 1. Typical U.K. vehicle dimensions for detailed classification.

Vehicle Class	Wheelbase (m) 1	2	3	Chassis Height Code	Overhang (m)
21-22	1.90-2.95	1.90-6.00	0.50-1.30	1, 2, or 3	0-12.75
51-55	1.90-3.51	3.76-15.0	1.05-2.50	0	0-12.75
41-46	2.96-9.20	1.90-3.75	1.05-2.50	Not used	0-12.75

ACCURACY OF DETAILED SYSTEM

In order to assess the accuracy of the detailed classification equipment, photographic logging of vehicles has been carried out at four test sites. Vehicle class, as identified from film, has been compared with the microprocessor class assignment for some 15 000 vehicles in rural and urban locations in order to determine the capabilities of the system in a range of traffic flow regimes. At other sites, classifier output has been compared with the results of manual classified counts.

Accuracy studies undertaken by TRRL at two rural sites, where free-flow conditions prevail, suggest that the overall accuracy of classification is about 92 percent (7). Accuracies are lower for certain classes of vehicle where particular problems are met in discriminating between similar parameters. University of Nottingham accuracy studies (8) indicate that under free-flow urban traffic conditions, overall accuracy remains quite high. However, as congestion levels, bringing slow-moving traffic and poor lane discipline, accurate classification becomes increasingly difficult.

The accuracy of each installation has been assessed by the compilation of accuracy matrices, which compare microprocessor and visual classification. Summaries of the matrices are provided in Tables 2 and 3, which indicate the accuracy of classification for the more common vehicle types. The results allow compensating errors betwen classes where they occur.

Table 2 shows that at the rural sites, despite

Table 2. Detailed classification accuracy under free-flow conditions.

	Rural Site[a]				Urban Site[b]			
Vehicle Class	Observed Total	Classifier Total	Error	Percentage of Error	Filmed Total	Classifier Total	Error	Percentage of Error
0	57	40	-17	30	127	61	-66	52
1	4159	3976	-192	5	5712	5979	+267	5
2	266	392	+126	47	781	508	-273	35
21-22	56	56	-	-	34	43	+9	26
31	319	357	+38	12	675	641	-34	5
32-35	43	43	-	-	121	128	+7	6
41-46	4	4	-	-	25	31	+6	24
51-55	71	70	-1	2	239	226	-13	5
61	39	41	+2	5	55	42	-13	24
N-classes	-	44	+44	-	1	99	+98	-
Missed	-	-	-	-	53	46	-	-

[a]Overall accuracy = 92 percent. [b]Overall accuracy = 90 percent.

Table 3. Detailed classification accuracy for experimental installations.

	Noncongested Conditions[a]			
Vehicle Class	Filmed Total	Classified Total	Error	Percentage of Error
0	23	12	-11	49
1	2103	1879	-224	11
2	283	483	+200	71
21-22	21	21	0	-
31	336	347	+11	3
32-35	55	44	-11	20
41-46	3	9	+6	200
51-55	112	98	-14	13
61	15	17	+2	13
N-classes	1	100	+99	-
Missed	64	23	-	-

[a]Overall accuracy = 80 percent.

the high overall accuracy, a major source of error lies in the classification of cars, vans, and light commercial vehicles. The physical similarity between cars and vans makes their separation difficult, so classification errors can be substantial. Under free-flow urban conditions, results are comparable with those for the rural situation, as indicated in Table 2. The problem of misclassification of cars, vans, and two-axle trucks is again apparent.

The serious underestimation of motorcycles (class 0) in Table 2 (urban site) is related to the use of commercial axle detectors that have low sensitivity and do not cover the full width of the lane. A new form of axle detector developed by TRRL has been used at other sites. This tends to reduce problems of motorcycle classification by its greater sensitivity and its coverage of the whole traffic lane.

Both urban and rural studies indicated that the most common causes of misclassification are related to vehicles changing lanes. Discrimination of cars, vans, and two-axle trucks is dependent on an estimation of chassis height; vehicles with higher chassis give weaker signals. The same effect can, however, result when vehicles cross the side of the loop rather than its center. Although special routines are provided in the detailed classifier to detect straddling vehicles and adjust their chassis-height values, the resulting classification was still not wholly satisfactory.

To help resolve these problems, reference was again made to the University laboratory study of loop zones of detection (5). Model tests and full-scale field trials led to the selection of a series-wound double rectangular loop in each lane, as shown in Figure 6. The tests indicated that more uniform length and chassis height measurements could be expected from these loops for a wider range of vehicle lateral positions. The new loops were installed at an experimental urban site with a high proportion of straddling vehicles following an upstream merge. Another feature of the site is congestion during busy periods.

Weaving at the two urban sites was compared by using the Golden River Environmental Computer system for precise timing of vehicles across three pneumatic tubes. Parallel tubes were used to measure vehicle speeds, and the time on a third, diagonal tube was used to indicate lateral position. Figure 7 shows the distribution of vehicle lateral positions at both installations; the higher proportion of straddlers is found at the experimental site.

Two separate accuracy studies were undertaken at this site during free-flow traffic conditions. The first, a routine comparison of microprocessor and film classification, indicated an overall accuracy of about 80 percent (Table 3). The reduced accuracy was clearly related to the high proportion of straddling vehicles, as shown for example in the number of cars wrongly classed as vans. It was not clear from these results whether the new loop design had helped to limit the problem of misclassification.

Further comparisons were therefore carried out by using a test vehicle at a range of lateral positions. The variations of loop output with lateral position for the conventional and experimental loops are shown in Figure 8. The experimental loops do give a more consistent signal over a wider range of lateral positions than the conventional loops. On the other hand, they do not cover as wide an area as had been expected from the experimental tests. One factor in this result appears to be interference between the fields of adjacent loops.

To summarize, the results of the tests on detailed automatic classification suggest that high overall accuracies can be obtained at many free-flow sites where the incidence of lane changing is low. Some classes of vehicle still create problems, and work is continuing on further improvements. Accurate classification under urban traffic conditions presents greater difficulties, and research in this area is at an earlier stage.

EVALUATION OF U.S. AUTOMATIC CLASSIFICATION SYSTEMS

Six automatic classification systems have been tested by the Materials and Research Division of the Maine Department of Transportation for the Federal Highway Administration (FHWA) (10). Standard accuracy checks were applied to six currently available systems. Five of these, including the Golden River four-bin length classifier, provided simple classification on the basis of axle configuration or vehicle overall length. The detailed classification system developed at TRRL was also tested at the Maine facility.

Accuracy checks included the cross-comparison of automatic classification listings with film records and the collection of summary data over longer test periods (overnight and over weekends).

Results for the simple classification systems indicated that the poor reliability of both the vehicle sensors and the classification equipment was a major source of error in vehicle identification. Pneumatic tubes were subject to both accidental and purposeful damage, which resulted in axle undercounting, and in addition poor signal definition from the air-switch units led to axle undercounting even when pneumatic tubes were not damaged.

Systems that used inductive loops for vehicle sensing were found to be oversensitive to minor adjustments of, or variations in, the loop-detector units. The tests with the Golden River four-bin length classifier were limited by equipment faults, but a small sample of results suggested that loop problems were less noticeable and that the measurement of vehicle overall length was generally more accurate.

It was noted that the classification schemes used in the various simple classification systems did not offer adequate detail when compared with the data-collection requirements suggested by FHWA. Not only were the schemes limited by the number of categories used, but there could be misleading overlap between the categories that were defined.

Tests with the TRRL detailed classification system indicated that many of the above problems were overcome through the use of both loop and triboelectric sensors. Specific accuracy checks indicated that overall and axle-length measurements were extremely good and that speed measurements were to within ±1.61 km/h (1 mph) of recordings made with radar equipment. In all, 98 percent of the 3000 vehicles checked were classified correctly, despite a much-reduced initial calibration procedure.

FURTHER DEVELOPMENTS IN DETAILED CLASSIFICATION

Additional research is currently in progress at both the University of Nottingham and TRRL to further improve the performance of the detailed vehicle classifier. Areas of interest include classification under congested traffic conditions, further improvements to sensor response for lightweight vehicles, further modifications to loop design for chassis height discrimination, and the classification and counting of bicycles.

Software development has been studied at the University by means of a classification simulation run on a minicomputer. Raw signals from the sensor array, recorded in conjunction with films of vehicle flow, provide data on which modifications to soft-

Figure 6. Experimental sensor configuration for detailed classification.

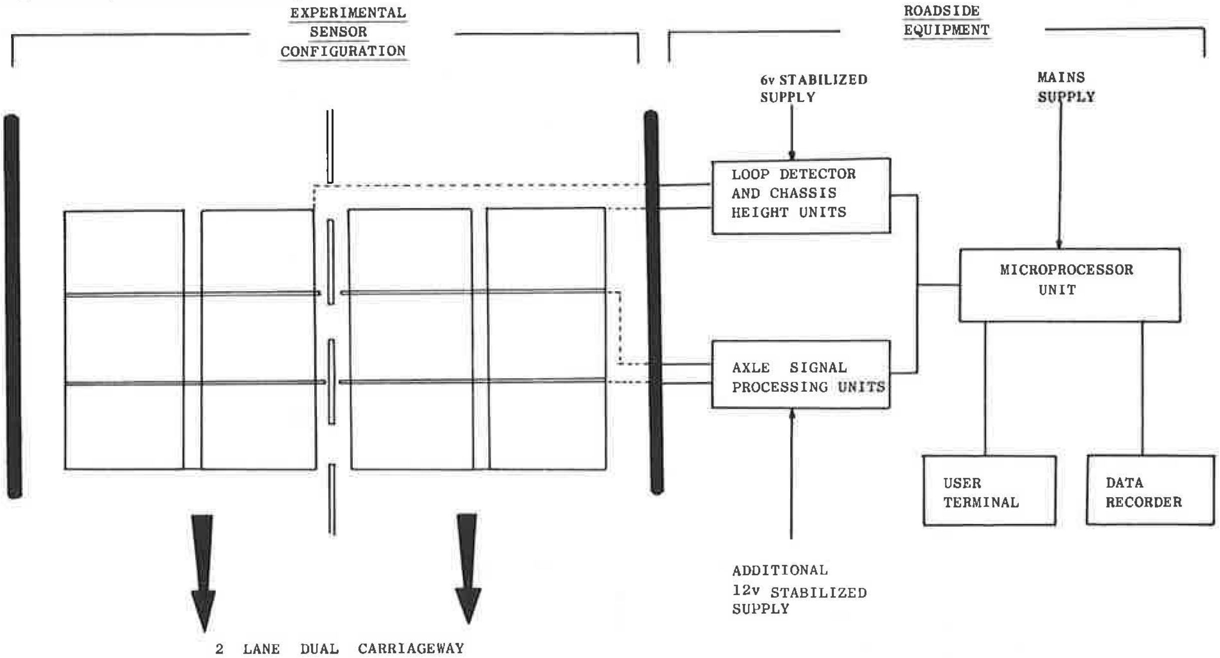


Figure 7. Distribution of vehicle lateral positions at two urban sites.

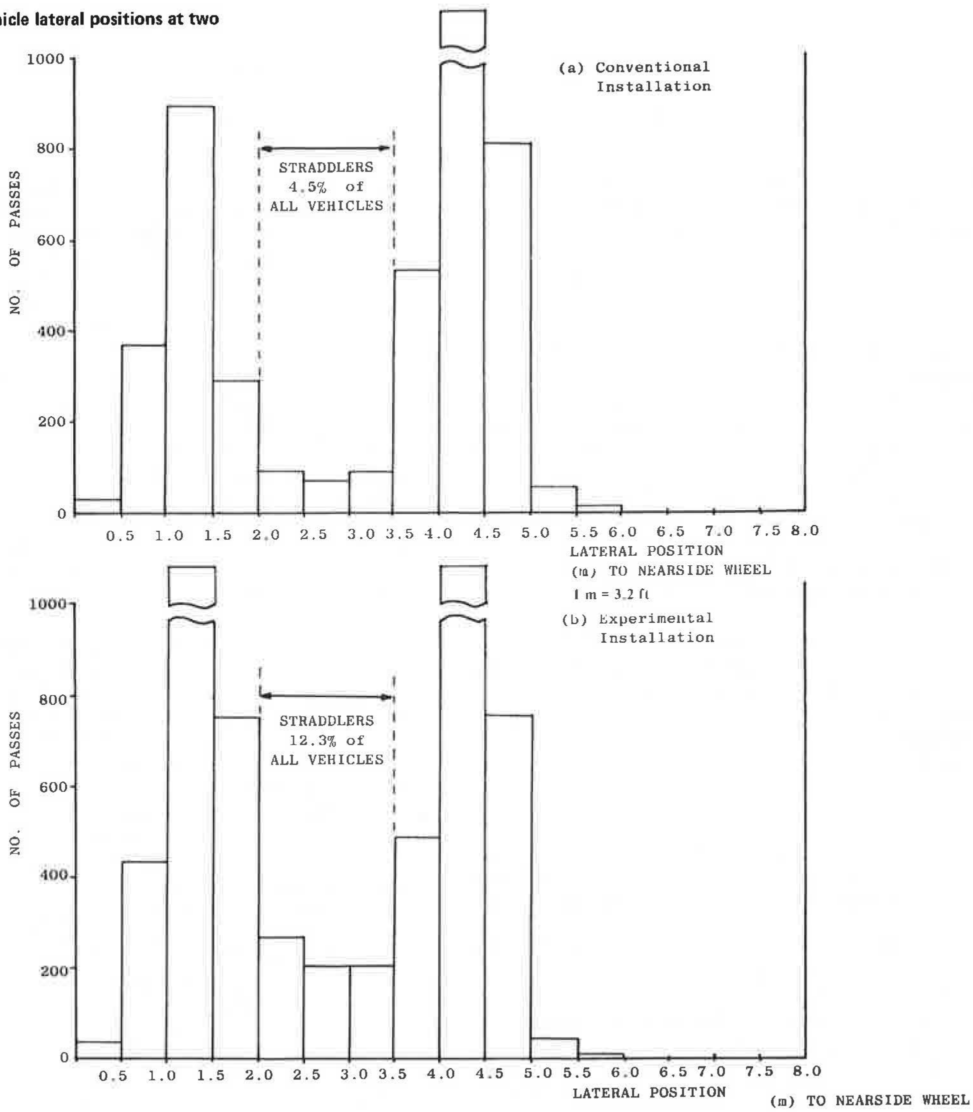
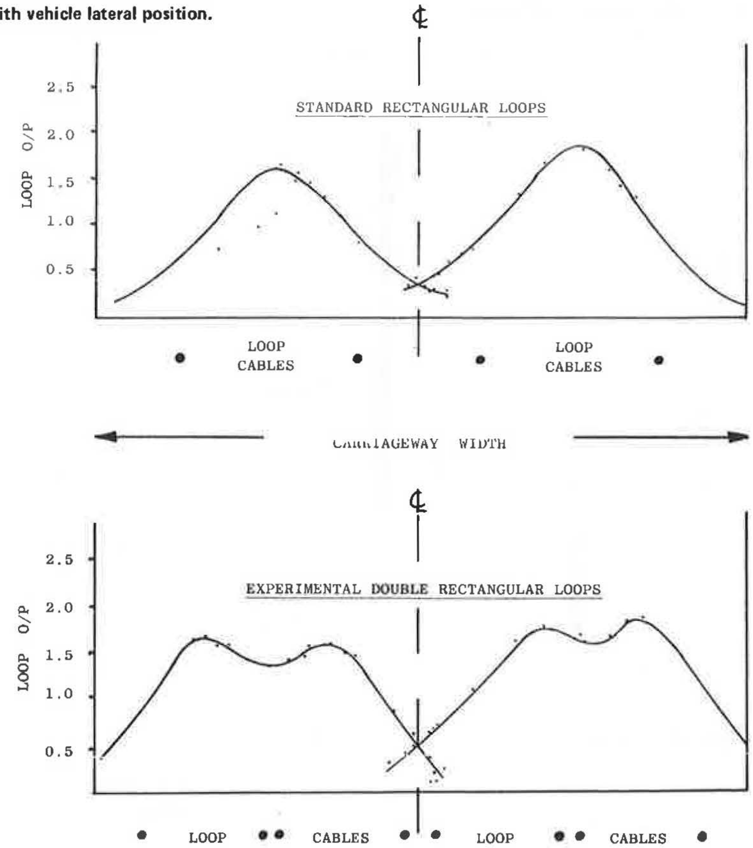


Figure 8. Variation of loop output with vehicle lateral position.



ware can be tested and appraised. Under experimental conditions, fine tuning of parameter boundary values and new procedures for dealing with unclassified vehicles have improved the accuracy of classification from 88 to 97 percent on a sample of 5000 vehicles. It remains to be seen whether these improvements will prove sufficiently robust to be transferable to routine conditions in the field.

The development of queue conditions over the vehicle sensors is known to cause a substantial reduction in the accuracy of classification. A major problem is the sensing of very slow-moving vehicles at the loops and axle detectors. Modifications to hardware are already in progress, and software development of special routines for congested conditions will follow in due course.

A final area of interest to many potential users of the system is the development of temporary sensors for a portable detailed classification system. Recent improvements to temporary loop sensors have resolved some problems in this area, but temporary axle detectors other than pneumatic tubes have yet to be developed to satisfactory standards. There are many possibilities for developments in this area and further work is currently proposed.

CONCLUSIONS

The evidence available on manual classification suggests that its accuracy is very much lower than might commonly be supposed. When coupled with the errors of sampling, scaling, and forecasting, the reliability of manual classified traffic count data must be seriously open to question.

The development of microprocessor equipment for traffic data collection makes long-term monitoring at increased numbers of survey points a practical proposition. Apart from the probability of improvements in classification accuracy by using automatic equipment, the increased coverage through space and time should lead to smaller sampling errors, which gives a more reliable base for the forecasting of future traffic levels. Furthermore, in conjunction with axle-load data, the availability of more detailed classified count information might also pay dividends in the fields of pavement design and highway maintenance.

The accuracy of simple vehicle classification by using loops alone may be limited more by the inherent properties of loop sensors than by the microprocessor equipment or software adopted in any particular case. Nevertheless, provided that classification sites are chosen well and on-site calibration is carried out with care, the evidence suggests that classification can be sufficiently accurate for the determination of PCE flows. Simple vehicle classification equipment that uses only pneumatic-tube sensors has been shown to be less reliable due to the susceptibility of these sensors to accidental or purposeful damage.

The detailed vehicle classification equipment, which uses loop and axle sensors, is now commercially available from the Golden River Corporation. Further developments to the system are currently under way in a number of areas, and progress can be anticipated in the extension of the system to a full range of urban sites as well as to portable equipment for temporary census points. The widespread application of these techniques may still be some years ahead, although some applications for routine traffic monitoring are already under way.

In the longer term, the falling cost of microprocessor equipment together with increasingly high labor costs point to an inevitable growth in the attractiveness of automatic vehicle classification techniques. Some of those techniques will be applied in the future; others are available now. If properly used, their application should lead to more reliable classified count data for highway planning and operation.

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Application of Counting Distribution for High-Variance Urban Traffic Counts

STEPHEN G. RITCHIE

This paper describes an application of the negative binomial counting distribution to high-variance, short-period traffic counts collected on urban arterial roads during peak-period flow conditions. The data were collected at four sites downstream from signalized intersections in metropolitan Melbourne, Australia, during 1977-1978. Alternative parameter estimation techniques are described as well as a simple method for dealing with transient traffic demand patterns. The results of these comparative evaluations suggest that the negative binomial distribution can be applied quite simply to commonly occurring problems that involve high-variance traffic counts and that results are often markedly better than those for other elementary counting distributions such as the Poisson distribution.

The inherent statistical variability of many flow-related attributes of urban transportation systems has important implications for the design, operation, and use of such systems, e.g., in transit service design (1), traveler mode choice (2,3), and delay at signalized intersections (4), to name only a few.

Moreover, continued emphasis on transportation systems management policies has increased the need for more accurate and realistic models that are useful for urban traffic systems analysis. Such models include basic statistical distributions of traffic characteristics such as vehicle headways, speeds, gap acceptances, and vehicle arrivals at a point, which are routinely used by traffic engineers and analysts in analyzing traffic system performance, designing and improving traffic facilities, and developing traffic simulation models.

This paper is concerned specifically with traffic-counting distributions, which describe the distribution of vehicle arrivals at a point during a given time interval. Gerlough and Huber (5) have described the elementary traffic-counting distributions, namely, the Poisson distribution, the binomial distribution, and the negative binomial (NB) distribution. These statistical distributions have been known to traffic engineers and analysts for some time. However, the NB distribution has not enjoyed the same wide application as the Poisson distribution to traffic problems, despite its apparent superiority under fairly common variable flow-rate conditions where the variance of traffic counts is high.

In this paper an application is described of the NB counting distribution to high-variance traffic counts and more specifically to short-period counts collected on urban arterial roads during peak-period flow conditions. Alternative parameter estimation techniques are described as well as an explicit but simple method for dealing with transient traffic demand patterns (i.e., time-varying traffic flow rates). The results of these comparative evaluations are presented.

STOCHASTIC NATURE OF URBAN TRAFFIC FLOWS

In an urban arterial road network, one of the major factors that influences the nature of vehicle arrivals on a link is the presence of upstream signalized intersections. The cyclic interruption to flow pro-