AUTOMATIC VEHICLE IDENTIFICATION AS A TRAFFIC MANAGEMENT MEASURE

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ABSTRACT:

This paper reviews the use of automatic vehicle identification and monitoring (AVI/AVM) as a traffic management measure. The technologies employed in AVI/AVM are discussed. AVM using transponders is a simple and practical method for vehicle identification and the implementation of an AVM system for electronic road pricing in Hong Kong is reported. It is argued that fitting transponders to private vehicles for the purpose of traffic management may not be politically or socially acceptable. A low cost scheme of vehicle identification is suggested in this paper. The scheme involves identifying wheelbase sequences rather than individual vehicles in a traffic stream. Correlation of the wheelbase sequences obtained from two axle detector pairs or stations will provide the journey time of the platoon travelling between the stations. Results from field tests indicate that a wheelbase resolution of 25 to 50 mm can be achieved. Three methods were developed from this scheme. The first method is the matching of wheelbase lengths on a cycle by cycle basis. It utilises the start times of green and red phases and was able to produce accurate estimates of link journey times. The other two methods, cross-correlation and least squares estimation, are more suitable for observation periods of 15 min and longer. They were found to be adversely affected by the presence of trucks. The least squares method is recommended for further refinement and incorporation as part of an ATC system.

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INTRODUCTION

Automatic vehicle identification (AVI) and automatic vehicle monitoring (AVM) have found many applications in traffic operations in recent years. These include the provision of priority for emergency vehicles or public transit, the collection of tolls on bridges and highways, access control for security reasons and the management of vehicle fleets. One recent application reported is an electronic road pricing system to discourage traffic in congested areas (Dawson 1983; Catling and Turner 1984). Experimental route guidance systems for assisting a driver to choose the best route to a given destination are also often reported (e.g. Yumoto 1977; Tomkewitsch 1984). It is argued that these techniques - AVI, AVM and route guidance - can reduce congestion, fuel consumption and pollutant emission in big cities.

With the availability of low cost and efficient microprocessors, it is now feasible to implement a wide range of techniques for vehicle identification. These include image processing and equipping vehicles with transponders. As AVI/AVM could be utilised as a real-time traffic management measure, it offers a new dimension to the traditional traffic signal control, which is concerned mainly with time management. With AVI, a continuous monitoring of the prevailing congestion levels is possible and dynamic space management by re-routing traffic in real time becomes feasible. Measures such as turn bans, lane allocation or even road pricing could be implemented at the most appropriate time and location. It should be recognised that there is now a real possibility to obtain from, and give feedback to, motorists information about prevailing traffic conditions, and hence to achieve some degree of voluntary re-routing to relieve congestion.

This paper is concerned with the monitoring of urban traffic congestion and, in particular, with the evaluation of area traffic control (ATC) system by means of vehicle identification. It begins with a discussion of the technologies employed in implementing AVI/AVM and the implementation of a pilot system for electronic road pricing in Hong Kong is reported. The relationship between AVI and the real-time evaluation of ATC systems is emphasised. While the use of on-board transponders for AVI is technically simple, its use may not be socially or politically acceptable. It may have to be restricted to government vehicles or public transit. A scheme that can automatically monitor the performance of a traffic control system without actually identifying individual vehicles is therefore preferable. However, this is a difficult problem since, in an urban road network, vehicles change lanes frequently and with traffic entering from and exiting into side-streets, the environment is 'noisy' for the purpose of estimating journey times from traffic flow. This paper proposes a scheme that involves identifying sequences of vehicles by their wheelbase lengths, rather than identifying individual vehicles. From this concept, the following three time series analysis methods are introduced:

(a) wheelbase matching;

(b) cross-correlation; and

(c) least squares estimation.

Real traffic data were used to test the validity of these methods. The results reported in this paper are based on data collected from a single road link in an ATC system. The analysis was therefore a univariate analysis with one pair of input/output time series. The results represent an initial attempt in this important area of research.

VEHICLE IDENTIFICATION

An AVI System

In a typical AVI system, a transponder is mounted on-board a vehicle and, if it is an active transponder that receives power from the car battery, continuously emits a coded signal. An interrogator or receiver unit installed by the roadside receives the signal via an antenna. The antenna can be pole-mounted or more commonly is in the form of an inductance loop embedded in the roadway. The code is then processed by a control unit which is usually housed together with the interrogator as a single piece of roadside equipment. Typically the control unit would be a traffic signal controller for implementing priority measures for buses and trams (Richardson *et al* 1978; Richardson and Ogden 1979; Sin 1984). The code emitted from a transponder may simply signify the presence or absence of the bus, or give more elaborate real-time information such as the current number of passengers on-board. Such information can be entered into the code by the bus driver and used by the traffic signal controller to implement the appropriate level of priority. If the transponder is a passive unit, it receives the power from the interrogator, usually via the inductance loop.

AVI using a passive transponder is a relatively new technology and can be based on various propagation frequencies, e.g. radio, microwave or optical.

An AVM System

An AVM system locates road vehicles within a well-defined geographical area and communicates to a control centre (it is sometimes called an automatic vehicle locating (AVL) system). The major application of AVM has been the real-time control and monitoring of vehicle fleets including buses, trams, police cars and taxis. Its use in buses and trams is particularly attractive because only fixed routes are employed and the location problem is much simplified. The potential benefits include an increase in operating efficiency by ensuring that vehicles are running on schedule and that advance notice is given to waiting passengers. Operational data can also be collected and stored efficiently, and in-vehicle security is improved.

A method commonly used for AVM is known as proximity detection (Skomal 1981) and requires on-board transponders for vehicle identification. Permanent devices known as signposts are positioned along the possible paths of vehicle movements in a monitored area. The number of signposts is determined by the desired position accuracy. Depending on how the transponder in a vehicle interacts with the signpost, two types of proximity detection are possible (see Fig 1). In a direct proximity AVM system, the approximate vehicle position data that a vehicle receives from a signpost is directly transmitted to the control centre by the on-board transmitter. If a VI code is transmitted to the signpost, the system is known as an indirect or inverted proximity AVM system. In this case, the signpost operates as an interrogator. The signpost sends the time of receipt and the VI code to the control centre via land-lines such as telephone lines. At the control centre, this code is related to the specific signpost to identify the location of the vehicle. Refinement of the above two techniques is necessary to determine the location of a vehicle between two signposts. Readers are referred to Skomal (1981) for these refinements and two other less commonly employed AVM methods known as dead reckoning and radio signal time difference determination.

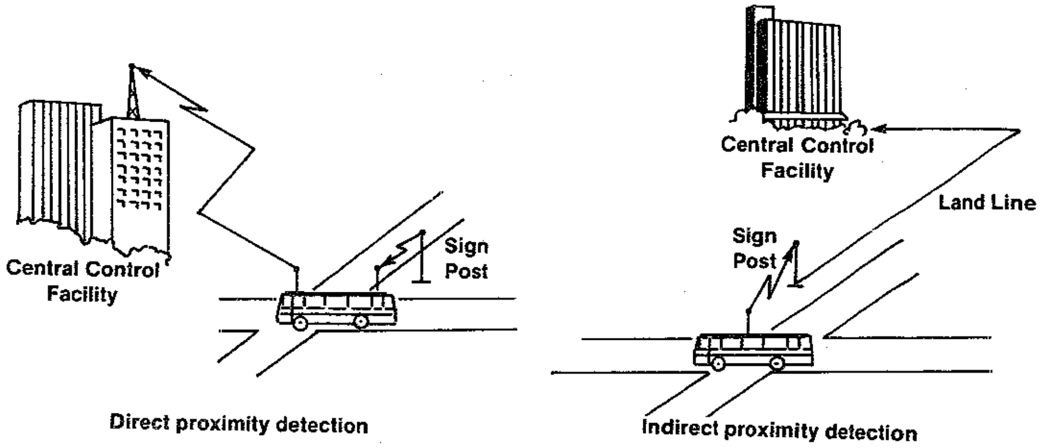

Fig 1 - Automatic vehicle monitoring (Skomal 1981)

A direct proximity AVM system for buses and trams is being implemented in Melbourne (Metropolitan Melbourne Tramways Board (MMTB) 1982). Simultaneously, the Sydney Co-ordinated Adaptive Traffic (SCAT) control system (Sims and Dobinson 1980) is also being implemented within the proposed AVM system. The desired AVM resolution in locating a vehicle is 15 s in time and 90 m in space, which limits its ability to implement vehicle-actuated priority measures at a signalised intersection. The interaction between SCATS and the MMTB-AVM systems will therefore be minimal. However, the feasibility of utilising the communication network of the SCAT system for monitoring trams, buses or any other vehicle equipped with transponders is recognised (Luk 1983).

ELECTRONIC ROAD PRICING (ERP)

A direct application of AVM using transponders is the implementation of road pricing in real time. Road pricing as a fiscal measure to reduce traffic congestion is not a new concept. The Area Licensing Scheme in Singapore has been in operation since 1975 (Watson and Holland 1978). The scheme requires that special supplementary licences be purchased and displayed on any car driven into a designated restricted zone during the morning peak commuting hours. Buses, goods vehicles, motor cycles, emergency vehicles and cars carrying four or more passengers are exempted. Thus, the Scheme is manually operated, whereas the proposed Hong Kong ERP System requires all vehicles to be encoded with transponders called electronic number plates (ENP).

The proposed ERP system is an indirect AVM system. Each vehicle is to be equipped with a passive transponder slightly larger than that of a video cassette tape. From this size, and the inductance loops cut on-site (Luk 1985), the frequency of transmission must be in the RF (radio frequency) range of 30 MHz to 1 GHz (although the exact frequency is kept as a secret to avoid vandalism). Two types of loops are used. The energising loop provides the energy to the passive transponder, which then transmits the vehicle identification code to be picked up by an adjacent receiving loop. The vehicle code, together with the time of activation and out-station number, are transmitted through telephone lines to a central accounting and control centre. The vehicle owner receives a monthly bill, which can be itemised if requested (at his own cost). A toll display adjacent to each out-station will also be used to remind a motorist of the toll at which he will be charged. A closed-circuit TV camera will also be utilised at each out-station to take photographs of any vehicle that is detected (by the inductance loop) but does not emit an acceptable code or any code at all.

A pilot system is currently being implemented in the central area on the north shore of the Hong Kong island. It consists of 20 out-stations and 3000 transponders. Most of these transponders will be mounted on government cars, but volunteers are being invited to offer their vehicles for tests in the pilot system. The cost of each out-station is estimated to be $1100 and that of a transponder is $60 each. The total cost of the pilot system would be around $6 m. The proposed final system will cover most of the urban area in Hong Kong. It would be about ten times the size of the pilot system and require 200 out-stations and about 300 000 transponders (i.e. the total vehicle population).

In comparison with increasing registration and licensing fees, road pricing is usually seen as an equitable fiscal measure. It does not affect car ownership. Each motorist can decide on individual economic grounds how much he wishes to pay for the use of congested roads. ERP would provide the flexibility of charging motorists in the most congested places and at the most appropriate times. Hong Kong also has the unique features that would make ERP a viable proposition. These include a small vehicle population of less than 300 000, a confined area and an efficient administrative structure for the registration and licensing of vehicles. Some of these conditions are not met in other countries. For example, in countries like Australia or the U.S., there will be too many inter- and intra-state vehicles and, unless all vehicles in a particular selected city are equipped with transponders, the ERP concept will not work. There will be too many vehicles that are detected but do not transmit any identification code; the task of checking through registration files even by computer is impractical. The question of intrusion into privacy is undoubtedly a sensitive issue. Public relation has to be properly handled and ERP must not be seen as another source of tax revenue.

Apart from ERP, automatic route guidance is another application of AVM. In fact, provision has been made in the proposed ERP system in Hong Kong to include route guidance as an option. Each electronic number plate already has an input port for the transmission of information from an out-station to a motorist if his vehicle is equipped with some form of video display. However, more research has to be undertaken before route guidance can be shown to be a cost effective traffic management measure. A typical example is the much publicised CACS system developed for Tokyo in the mid-seventies (Yumoto 1977) and yet now known to be abandoned (Luk 1985).

A more immediate problem is the estimation of traffic congestion without the use of transponders, and feeding-back to the motorists of prevailing traffic conditions. The feeding-back process can be achieved reasonably easily by broadcasting in specially allocated channels from low-power, short-range (say, 500 m to 1 km) roadside transmitters. The rest of this paper is devoted to the prime objective of VI for the specific aim of on-line evaluation of ATC systems without the use of transponders. Naturally, the concept need not be restricted to such an application and can be adopted for monitoring urban traffic congestion in general.

VEHICLE IDENTIFICATION AND EVALUATION OF ATC SYSTEMS

Evaluation of ATC systems are usually carried out by methods such as the floating-car technique, car number plate surveys and aerial photography. All these methods are manual and labour intensive and can only be carried out for a short period of time. A typical survey for comparing two methods of ATC would last for a period of 20 days, with eight survey hours per day, and weekends and after-business hours are not included. Consequently, manual survey methods are regarded as being incomplete and expensive (Luk, Sims and Lowrie 1983) and are therefore seldom undertaken on a regular basis.

AVI/AVM constitutes a potential category of evaluation method. However, such an approach would only be better than the floating-car method if a large number of vehicles were equipped with transponders. These vehicles would have to travel within the ATC network frequently or the samples available might not be sufficient for an accurate real-time evaluation of the performance of the control system. A scheme whereby vehicle travel times can be obtained in large quantities and without identifying individual vehicles, i.e. a vehicle non-identification scheme, is therefore desirable. Such a scheme is described below.

This scheme relies on an accurate measurement of the wheelbase of a vehicle. The wheelbase is an invariant quantity in mathematical terms and therefore allows a vehicle to be traced through a road network within reasonable distances. Figure 2 illustrates the scheme for measuring the journey times of a platoon of vehicles between two locations (A and B) in an ATC network. Two axle detectors separated by a distance L are used to determine the speed and wheelbase of a vehicle passing over each detector pair, or station, at A and B. The premise of the proposition is that sufficient information can be obtained by studying a sequence of wheelbases rather than a single vehicle or wheelbase. The correlation of the wheelbase sequences obtained at the two stations provides a measure of the platoon journey times between them. By repeating the process between all adjacent intersections in an ATC network, the performance of the control system can be ascertained. Depending on the traffic flow, this scheme will provide several journey time samples per signal cycle. It is therefore far superior to the floating-car method, which usually only provides one to two samples per 15 min.

The detectors, both upstream and downstream of an intersection, are laid in a lane with representative link traffic flow. If more than one lane needs to be studied, more axle detectors are required and a simple logical operation is needed to determine the lane choice of each vehicle. Alternatively, a pair of loop detectors can be used to calculate vehicle lengths, which can similarly be used for matching. Each detector pair should ideally be located at a position where either the speed or the acceleration/deceleration rate of each vehicle remains reasonably constant within the detector spacing L. An appropriate choice would be a position beyond the maximum queue length formed at the stop-line in each signal cycle. The stop-line would appear least appropriate because vehicles tend to slow down to join the queue and then accelerate off from the intersection.

Figure 3 illustrates the four positions of a vehicle crossing a detector pair. Assuming that the vehicle travels at constant speed, the speed v and the wheelbase w are given by:

$$\left.\begin{aligned} \text{speed } v &= L \,/\, T_{34} \\ \text{wheelbase } w &= v.T_{13} = L.T_{13}/T_{34} \end{aligned}\right\} \quad (1)$$

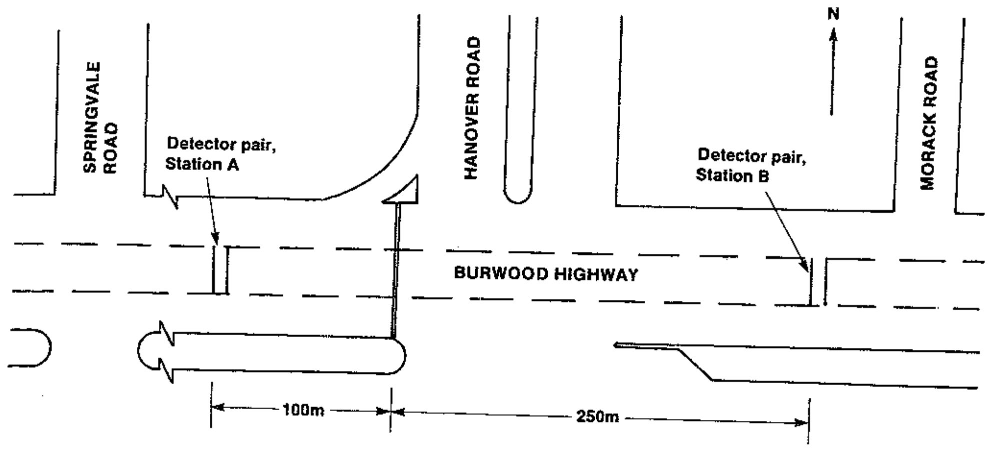

Fig 2 - Vehicle identification using two axle detector pairs at Burwood Highway site (not to scale)

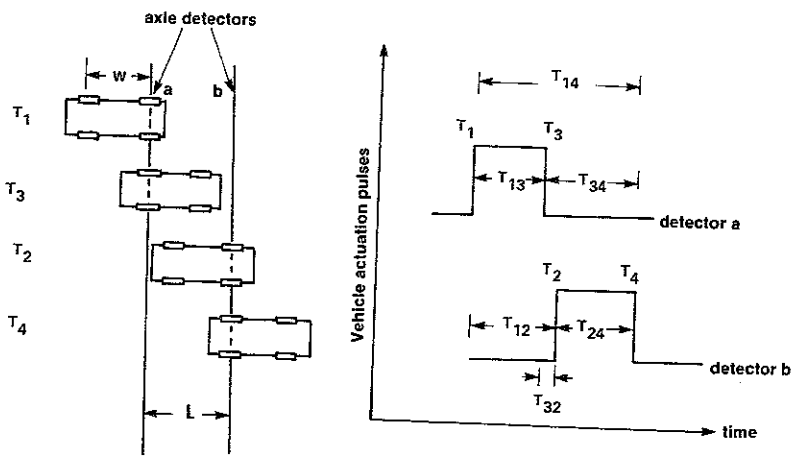

Fig 3 - Four positions of a vehicle passing over two detectors

The variables are as shown in Fig 3. If the vehicle accelerates with a constant rate across a detector pair, the instantaneous velocity becomes a function of time and the wheelbase is given by:

$$w = \frac{L.T_{13}}{T_{24} + T_{13}} \cdot \left[\frac{T_{14}}{T_{12}} + \frac{T_{23}}{T_{34}}\right] \quad (2)$$

Equation (2) was reported in Gazis and Foote (1969) for identifying car lengths in the Lincoln Tunnel in New York. They used optical detector pairs for vehicle identification and then determined the exact number of vehicles at various sections of the tunnel. They attempted to control the flow to an optimum value of 1320 cars per lane per hour. The scheme proposed in this paper for ATC system evaluation utilises a similar concept for VI, although the traffic operating environment is much more difficult because lane-changing and side-street traffic will introduce 'noise' into a wheelbase sequence.

The proof of eqn (2) can be found in Luk (1983), in which some existing data collected in another ARRB study for wheelbase determination was analysed. The wheelbases calculated using constant speed and constant acceleration assumption were compared. Twenty four sample sets of wheelbases from two detector pairs were used to obtain the correlation coefficient and the standard deviation of the differences. Using eqn (1), the correlation coefficient and standard deviation are 0.969 and 102 mm respectively. The corresponding values using eqn (2) are 0.982 and 69.3 mm. Hence, the constant acceleration assumption usefully improves the correlation of the wheelbase sequences and eqn (2) was used in all field studies described below.

WHEELBASE MEASUREMENT

A series of field studies was carried out at sites in Burwood Highway, Vermont South, as already shown in Fig 2. The ARRB Vehicle Detector Data Acquisition System (VDDAS) was used to record the times of actuations as vehicles passed over the axle detectors (see Fraser 1981). The detectors were of the treadle type made of metal strips suitable for field studies of short durations. Detectors were spaced at 3 m and 4 m apart in day 1 and at 5 m and 6 m apart in day 2 of the field studies. The middle lane in the east-bound or p.m. peak direction was chosen as the representative lane for monitoring platoon journey times. The separation of the detector pairs A and B in Fig 2 was limited by the length of cables available for linking the axle detectors to VDDAS. A value of 350 m was chosen. Data was collected in two afternoons from about 3 p.m. to 5 p.m. - a period corresponding to the transition from off-peak to peak flows. The start times of green and red phases were also manually keyed into the data logger for processing later. These times are easily available from an ATC system if the proposed scheme is incorporated as part of the system. The aims of the field studies were as follows:

(a) To study the distribution of wheelbase in an urban arterial road environment;

(b) To determine the optimal spacing (L) between two axle detectors; and

(c) To study the feasibility of correlating the upstream and downstream wheelbase sequences.

Distribution of Wheelbases

Table I presents the wheelbases of twelve car models in Australia. They are obtained from manufacturers' data and range from 2000 to 3000 mm. The proposed vehicle identification scheme would benefit from a uniform distribution of wheelbases in that range. In this case, a Commodore with a wheelbase of 2668 mm would be as likely to be followed by another Commodore as by a Honda Civic with a wheelbase of 2250 mm. The task of correlation would then be much easier and the resolution of the measuring system would be less critical. The distribution of wheelbases determined from data collected in the two afternoons at the upstream station A is shown in the histogram in Fig 4. The total number in the sample was 2194 and the distribution had two peaks at 2500-2600 mm and at 2800-2900 mm and was reasonably even in the 2300 to 3000 mm range. Seven per cent of the wheelbases were longer than 3000 mm and would be particularly useful as markers for VI. The observed distribution suggests that VI by the wheelbase is a viable proposition.

Optimal Spacing Within A Detector Pair (L)

The data collected for establishing the feasibility of correlation was firstly used to determine the optimal value of the detector spacing, L, within a detector pair. If L is too large, speed variation within it will violate the assumptions of constant speed or acceleration and hence the accuracy of eqns (1) or (2). If the spacing is small, the resolution of the measuring equipment becomes critical. The resolution of the ARRB VDDAS for axle detection is about 1 to 2 ms and additional variation comes from differences in tyre pressures, duration of contact between the tyre and the axle detector, and the possibility that the detectors are not perfectly parallel. At $L = 3$ m, and at a speed $v = 13$ m/s, the duration of the pulse $T = 3/13$ s = 230 ms. A resolution of 1 ms therefore constitutes 1/230 or 0.4 per cent error. Using eqn (1), the error would be at least twice or roughly 1 per cent. At a wheelbase of 2500 mm, this error becomes 25 mm.

The correlation coefficient and the standard deviation of the difference between matched pairs of wheelbases were computed at four levels of tolerance. The results are shown in Fig 5. The optimal value of L at each tolerance level is identical and is 5 m. The variation in the number of matched pairs is shown in Table II. At all values of L, there were large increases in the number of matched pairs as the tolerance was increased from 25 to 50 mm. At $L = 5$ m and at a tolerance level of 50 mm, the sample size was (252+55) = 307, and was 96 per cent of all matched pairs with a tolerance level below 100 mm. These results confirm that the majority of vehicles in a platoon can be uniquely identified by their wheelbase lengths if the measurement system has a resolution better than 50 mm. The increase in tolerance beyond 75 mm may introduce errors in the correlation process - two vehicles in the same platoon but of different wheelbases may be wrongly identified as the same car.

TABLE I

WHEELBASES FROM MANUFACTURERS' DATA

Model	Wheelbase in mm
Honda Civic	2250
Charade	2300
Datsun Sunny	2340
Corolla	2400
Gemini	2404
Datsun 200B	2500
Sigma	2515
Toyota Corona	2525
Cortina	2578
Commodore	2668
Falcon	2790
Valiant	2820

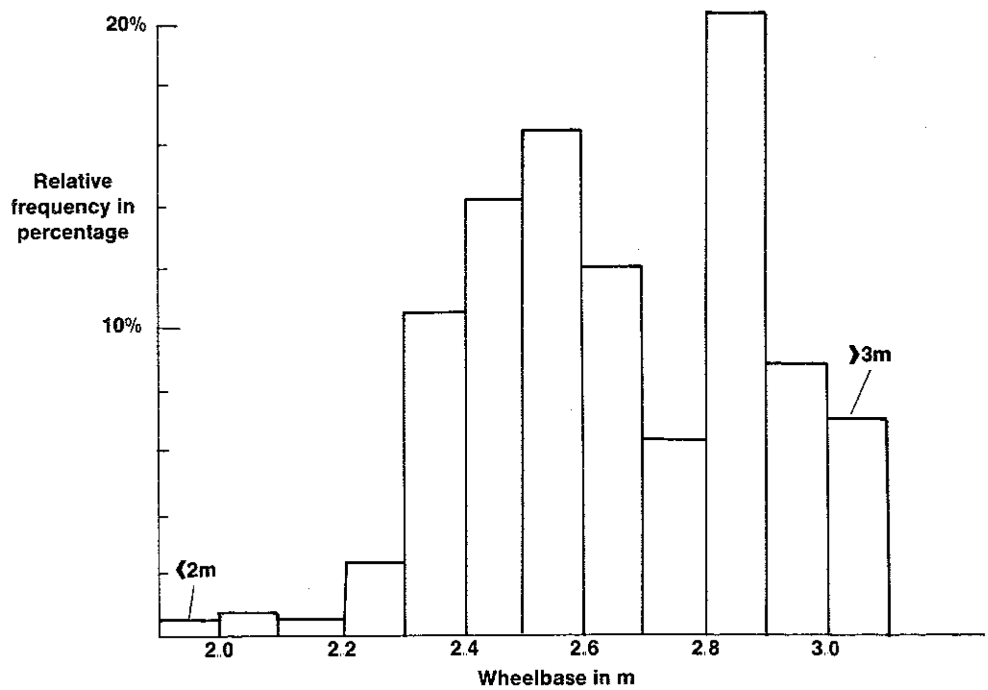

Fig 4 - Distribution of the wheelbase data collected

TABLE II

VARIATION OF SAMPLE SIZE OF MATCHED WHEELBASES WITH TOLERANCES

Detector Spacing L	Sample Size Tolerance = 25mm	Increase in sample size Tolerance = 50mm	75mm	100mm	Total
3m	135	67	7	10	219
4m	234	62	15	0	311
5m	252	55	11	2	320
6m	275	57	3	5	340

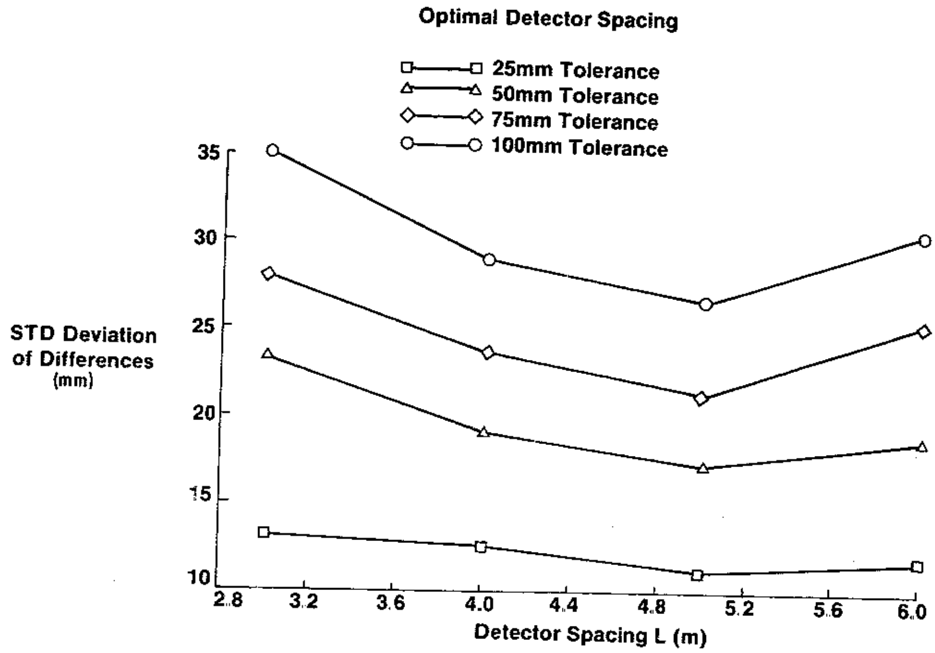

Fig 5 - Optimal spacing within a detector pair

From the results obtained, it is clear that most wheelbases in a traffic stream can be uniquely identified with an equipment that has a resolution better than 50 mm. Based on this concept of utilising wheelbase as an entity for identification, three methods were investigated: wheelbase matching, cross-correlation and least squares estimation.

WHEELBASE MATCHING

Simple matching processes, where a single wheelbase recorded at station A is matched to a wheelbase at station B, and journey time calculated, were the first methods examined for journey time estimation.

The raw data from axle actuations, collected by the VDDAS system, was processed by a FORTRAN computer program. For each station, this program produced a formatted file containing, for each vehicle, the wheelbase and actuation time of the first detector of the pair. Red and green times which had been manually entered via the VDDAS keyboard were interspersed in the data. For the purpose of further analysis, the data collected in day 2 using 5 m and 6 m detector spacing was split up into 7 time periods, each 15 min in length, with the exception of the final period for each detector spacing. These two periods were each slightly less than 15 min. These time periods, and the sample size in each, are detailed in Table III. Due to the similarity of the data sets collected in days 1 and 2, the results from day 2 only are reported.

TABLE III

15 MINUTE TIME PERIODS OF DATA

	TIME INTERVAL	NO. OF VEHICLES -			
		CARS	TRUCKS	TOTAL	%TRUCKS
5m DETECTOR SPACING	1	118	16	134	12
	2	129	16	145	11
	3	146	14	160	9
	4*	121	14	135	11
6m DETECTOR SPACING	5	163	13	176	7
	6	199	13	212	6
	7*	203	18	221	9

* slightly less than 15 min period

The first process undertaken with this data was the 'manual matching' of wheelbases between the two stations. This was done for two reasons:

(a) To determine a 'model' answer to which later results could be compared; and

(b) To aid in the development of an algorithm so that the matching process could be automated.

The manual matching process consisted of the following steps:

(a) Wheelbase and actuation time for each station were printed out side by side.

(b) Using the red and green times, this data was split up into platoons. Only vehicles which were members of a platoon and which did not stop at the signals were considered, to ensure that the measured journey times represented those of the major movement in the ATC system.

(c) A vehicle at station A was considered to be matched by a vehicle at station B if (i) it was a member of the same platoon, and (ii) it had a wheelbase within the tolerance of 50 mm. The sequence of wheelbases was assumed, for this particular site, to have retained the same order, i.e. while vehicles may have moved into or out of the lane, it was assumed that no vehicle would have overtaken another and then moved back into the same lane again. Where there were several vehicles with similar wheelbases (within the tolerance of 50 mm) which could all possibly match, headways were calculated, and vehicles were chosen in such a way that headways were preserved as closely as possible.

Due to the tedious nature of this manual processing, it was done only for period 1 (approximately 10 platoons).

Matching of vehicles which were not members of the same platoon was also investigated. Vehicles which were stopped by a red signal at station A, either 'left-over' at the end of a platoon, or which had entered from side streets between platoons, would be expected to appear at the start of the next platoon. This type of matching could be expected to provide information about delays encountered by vehicles which are stopped by the signals. Examination of the data revealed very few vehicles which were forced to stop at the red signal following station A, due to the strong platooning from the upstream signals at Springvale Road and the small volume of side-street traffic entering between Springvale Road and station A. Unfortunately, this meant that there were too few vehicles at this site to provide any useful data, so this type of matching was not pursued further.

The next task was to write a program to automate the matching process, so that large amounts of data could be handled. The program operated in the following manner:

(a) The vehicle data was split into platoons, using the manually entered red and green times. Only vehicles arriving at A which were members of a platoon, and did not stop at the red signal were considered. Vehicles at A were only matched to vehicles at B that were members of the same platoon, to avoid erroneous matching with vehicles entering from the side-streets during the red. Platoons were defined as follows: (i) platoon at A consisted of vehicles arriving any time between 5 s before the green and 1 s after the red, and (ii) platoon at B consisted of vehicles arriving any time between 14 s after the green and 26 s after the red. This range was wide enough to capture the majority of vehicles travelling within the observed speed range. These times were determined by examination of headways in the data. It was decided not to use headways in the program as a basis for selecting platoons, as a large gap between platoons does not always occur due to random entry of side-street traffic into the major traffic stream.

(b) An <u>observation window</u> was determined from the manually matched data. This period was determined from the minimum and maximum journey times from A to B. Vehicles were only matched if they were detected at B within the observation period. The period chosen was from 12 s to 25 s. This represents a speed range of 50 km/h to 105 km/h.

(c) A tolerance of 50 mm was used to match vehicles. The data for a vehicle at station A was read. If it was not part of a platoon, it was discarded. Otherwise, a matching record was then sought at station B that was in the same platoon, within the observation period, and had a wheelbase within 50 mm, and had not already been matched to a previous vehicle at station A. If a match was found, data from both stations was written to an output file. The next record from A was then processed.

(d) A running total of the number of matched vehicles was kept during this process so that the proportion matched could be calculated.

(e) Having produced a file of matching vehicles, another program was used to process this file and calculate the mean journey time platoon by platoon, and the mean journey time for the whole period (generally 15 min) covered by the data.

Platoon by platoon results for the first 15 min are listed in Table IV. Comparison with the 'manually matched' results shows lower means for some platoons. This is due to the fact that the program selected the first matching record at station B that satisfied all of the given conditions. The 'manually matched' data considered headways between vehicles and this sometimes led to the choice of a vehicle later in the platoon. The difference between the two sets of mean journey times was 2 per cent. This was not considered significant enough to justify the extra programming necessary to incorporate consideration of vehicle headways. This matching program, the first method attempted for obtaining journey times automatically from wheelbase data, was thus considered to give a good estimate of the 'true' journey time. The next stage was to look at 15 min periods of data, comparing other methods of obtaining journey times, using this matching program as a basis for comparison.

TABLE IV

JOURNEY TIMES PLATOON BY PLATOON

	Platoon	Manual Matching		Matching Program	
		Mean	S.D.	Mean	S.D.
	1	19.0s	2.2s	19.2s	2.1s
A	2	19.0	1.3	19.0	1.3
L	3	20.7	2.0	20.2	2.1
L	4	20.7	2.7	19.8	1.1
	5	19.4	0.5	18.9	1.4
V	6	19.4	1.9	17.6	2.4
E	7	17.9	1.8	17.9	1.8
H	8	17.7	2.4	17.7	2.4
S	9	19.5	2.5	20.5	3.6
	10	19.0	2.0	18.0	3.8

CROSS-CORRELATION ANALYSIS

A novel approach to obtaining the platoon journey time was then investigated, using the same data as had been used in the matching processes previously discussed. This approach was motivated by work which had used the cross-correlation function for delay measurement in industrial processes (e.g. Box and Jenkins 1976; Kenyon 1983), and proceeded as follows. Firstly, the sequence of wheelbases at each station was expressed as a time series, that is, a series of measurements at regularly spaced time intervals. The cross-correlation coefficient (see eqn (3)) was then calculated for the two time series at values of lag, τ , ranging from well below to well above the anticipated journey time. The lag which gave the highest value of the cross-correlation coefficient was then taken as the average journey time. The cross-correlation coefficient is defined as:

$$r_{xy}(\tau) = \frac{c_{xy}(\tau)}{s_x s_y} \qquad \tau = 0, \pm1, \pm2, \pm\ldots \tag{3}$$

where s_x and s_y are the standard deviations of N pairs of x_k and y_k values with zero means, and $c_{xy}(\tau)$ is the cross-covariance of y given x at lag τ :

$$c_{xy}(\tau) = \frac{1}{N} \sum_{k=1}^{N-\tau} x_k \cdot y_{k+\tau} \qquad \tau = 0,1,2,\ldots$$

The first step was to develop a program to prepare the data in suitable form for input to the correlation function. The data had been processed into the form of a formatted file, containing wheelbase lengths and actuation times for each station, by programs previously discussed. The cross-correlation function requires data in the form of a series of measurements, taken at regularly spaced or sampling time intervals, dt. To achieve this, it was necessary to intersperse the data with zeros to provide a data point for every time interval. A simple FORTRAN program was written which, for each time interval in the range of interest, wrote the wheelbase value if one had been recorded at that time, and otherwise wrote a zero for time intervals where no wheelbase was recorded. The value of dt therefore represents the time resolution of the detector information.

These series were then processed by a cross-correlation function. Initial work was done using a function from the IMSL(1980) library, FTCROS, but later a FORTRAN program was developed to calculate the values of the cross-correlation function, to allow more flexibility in processing.

Initial tests were done using data from a single platoon, and some conclusions were drawn regarding the most suitable time interval. The program used to prepare the data for correlation could be made to write data points at user-specified intervals. Figure 6 illustrates the decrease in spurious correlation with increasing time interval. Figure 6a (0.5 s interval) shows several spurious peaks, including one greater in magnitude than the peak at the expected lag value. Comparing Fig 6b (1 s interval), we see a reduction in magnitude of the spurious peaks relative to the desired' peak. Over the range of interval values considered, 0.1 s, 0.5 s, 1 s and 2 s, the same trend was noted, with a steady decrease in the number of spurious peaks and their magnitude relative to the desired peak. Intervals greater than 2 s were not used, due to the fact that more than one wheelbase may have been measured during a longer interval, and hence information would be lost. Also, knowing the average journey time for the test site was approximately 20 s, a resolution better than 2 s would be required.

By chance, the data for the first platoon gave peaks (using 1 s and 2 s interval) at lag values near the expected value of the average journey time. This was not usually the case. Due to the inability to obtain consistent results on a platoon by platoon basis, further work was done with 15 min or longer periods of data. The improvement using longer periods of data is illustrated in Fig 7.

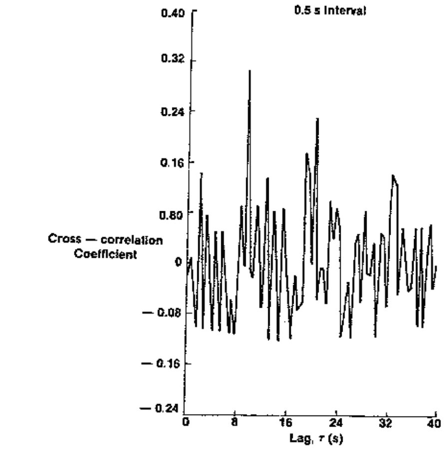

Fig 6*a*

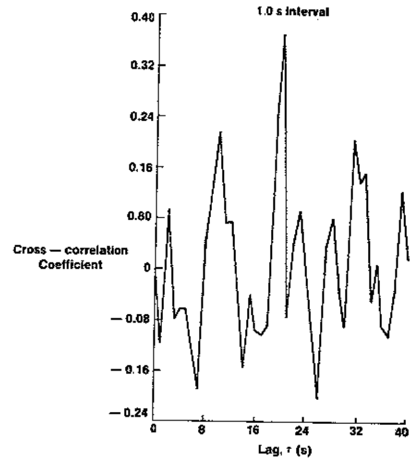

Fig 6*b*

Fig 6 - Cross-correlation coefficients vs. lag for one platoon using two different sampling time intervals

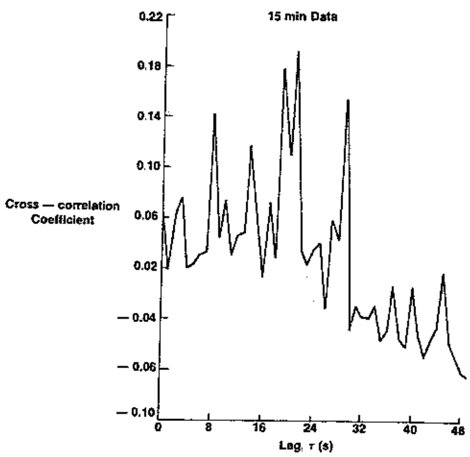

Fig 7*a*

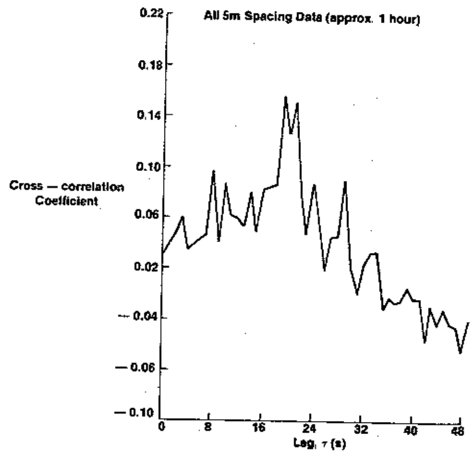

Fig 7*b*

Fig 7 - Cross-correlation coefficients vs. lag for different data periods

Comparing Fig 7a, obtained from 15 min of data, and Fig 7b, obtained from approximately 1 h of data, we can see the reduction of spurious peaks brought about by use of a greater amount of data. Figure 6b, which uses the same sampling interval of 1 s, may also be compared with Fig 7 to illustrate the effects of a relatively brief period of data, as it was calculated for one platoon, representing approximately 90 s of data.

One problem which rapidly became apparent was that of undesired peaks at lag values which were much higher or lower than the expected value. Investigation of the data showed this to be due in many cases to vehicles with long wheelbases producing large products when multiplied with lower wheelbase values. Several subsets of data were tried both with and without truck data (a wheelbase value greater than 3.2 m was used as a criterion). The correlation function appeared far more likely to give a single definite peak when truck data was discarded. Results of the cross-correlation (the time lag which gave the highest peak) are listed in Table V, along with the journey times calculated by the matching program.

TABLE V

MEAN JOURNEY TIMES FOR EACH PERIOD, BY COMPUTER MATCHING AND CROSS-CORRELATION

	Time Period	No. Matched	Propn. Matched	Matching Prog. Mean	Matching Prog. S.D.	Cross-correlatn dt=1s	Cross-correlatn dt=2s
ALL VEH	1	69	0.51	18.8s	2.5s	21s	18s
	2	97	0.67	19.3	2.2	21	22
	3	95	0.59	19.3	2.3	16	18
	4	80	0.60	18.8	1.8	19	22
	5	109	0.62	19.6	2.3	28	6
	6	125	0.59	20.1	2.1	28	28
	7	130	0.59	20.0	2.5	19	20
NO TRUCK	1	62	0.53	18.6	2.5	20	20
	2	89	0.69	19.2	2.1	20	16
	3	92	0.63	19.3	2.3	18	14
	4	75	0.62	18.8	1.9	17	18
	5	107	0.66	19.5	2.3	18	18
	6	121	0.61	20.1	2.0	19	16
	7	128	0.63	20.0	2.4	19	18

Examination of the cross-correlation results, firstly with trucks included, shows obviously incorrect results for several time periods; these are the 'undesired peaks' referred to previously. This problem, inherent in the cross-correlation process, can be minimised by the removal of trucks from the data. However, this means that we are discarding wheelbase information in the scheme, and possibly biasing the results towards a faster average journey time, assuming that trucks in general travel more slowly. The results with trucks excluded are more encouraging, with the 1 s interval results giving values of the desired magnitude. (All lie within one standard deviation of the mean estimated by the matching program). The 2 s interval results are less consistent, due to the loss of information about individual vehicles, as more than one vehicle may have been recorded during a 2 s period.

Looking at the 1 s results, the trend in journey times estimated does not follow that indicated by the method of wheelbase matching. There are two factors which could explain this lack of consistency: (i) the wheelbase data contains a low frequency 'seasonal component' due to the cyclic nature of the traffic, which is controlled by signals, and (ii) the noisy environment from which the data comes. The noise/signal ratio (N/S) is defined as the ratio of the sum of cars entering the route between input and output, to the sum of cars flowing from input to output (Strobel 1977). This ratio can be estimated as follows: the total number of vehicles passing through station B during the whole seven time periods was determined from the data to be 1257. The total number matched is 705, and this is assumed to be the number flowing from input to output. The difference between these two numbers is thus the noise, in this case, 552 vehicles. Hence, the N/S ratio in this case is calculated as 0.8. This is very noisy, and the probability of error at such a high N/S ratio is significant.

LEAST SQUARES ESTIMATION

Another time series approach is to formulate the estimation of link journey times as a system identification problem. The traffic link is considered as a transfer function that can be analysed in the time domain as in this paper, or in the frequency domain as in Ng and Luk(1983). The input to the transfer function is a time series collected from the upstream detector station A ($x_e(k)$), and the output is that collected from the downstream station B ($x_a(k)$). k is the index for the time series with a sampling time interval of dt, the time difference between two consecutive k values.

The following formulation of a model for estimating the average journey time between two detector stations was originally proposed in Strobel(1977). In his analysis, Strobel used traffic flow in the input/output series. In this paper, both the wheelbase and flow data were investigated.

Let the input vehicles $x_e(k)$ be delayed by time T which, from local traffic conditions, would have a minimum and a maximum value, i.e.

$$\left.\begin{aligned} T_{min} &= m.dt \\ T_{max} &= n.dt \\ \text{and } T_{min} &\le T \le T_{max} \end{aligned}\right\} \qquad (4)$$

Let $g(j)$ = percentage of cars reaching the output in the time interval $(j-1).dt \le T \le j.dt$, where $j=m,\ldots,n$. Then the model output $x_{aM}(k)$ can be conceptually represented as:

$$x_{aM}(k) = g(m).x_e(k-m) + \ldots + g(n).x_e(k-n) \qquad (5)$$

$g(j)$'s are called the <u>impulse response parameters</u> of the transfer function representing the traffic link. It is assumed in eqn (5) that each $g(j)$ is independent of time k within a measurement period of, say, 15 min. Define a <u>split coefficent</u> as follows:

$$h(n) = \sum_{j=m}^{n} g(j) \qquad (6)$$

Thus $h(n)$ sums up the percentages of cars departing from the origin station A at various times k in the range $[m,n]$. It therefore represents the ratio of cars entering the link via A and leaving it via the destination station B. It is hence an element of an origin-destination (O-D) trip matrix and has the conceptual property that

$$0 \le h(n) \le 1$$

Note that $h(n)=1$ means that all vehicles that pass through A will reach B and, similarly, $h(n)=0$ means that no vehicles will reach B after passing through A. With $h(n)$, it is possible to define the probability distribution function as:

$$F(j)=h(j)/h(n)=\text{Prob.}[T\le j.dt]$$

and the probability density function as:

$$f(j)=g(j)/h(n)=\text{Prob.}[(j-1).dt\le T\le j.dt] \qquad (7)$$

Hence, the average journey time is given by:

$$\bar{T} = \sum_{j=m}^{n} (j.dt).f(j) \qquad (8)$$

In matrix notation, with N as the number of sample points in a time series, eqn (5) can be expressed as:

$$\begin{bmatrix} x_{aM}(k) \\ \vdots \\ x_{aM}(k-N) \end{bmatrix} = \begin{bmatrix} x_e(k-m) & \ldots & x_e(k-n) \\ \vdots & & \vdots \\ x_e(k-m-N) & \ldots & x_e(k-n-N) \end{bmatrix} . \begin{bmatrix} g(m) \\ \vdots \\ g(n) \end{bmatrix}$$

or simply as:

$$\underline{x}_{aM} = \underline{U}.\underline{g}$$

As an example, let the input sequence consist of 100 sample points, i.e. k=0,....,99 and m=5, n=10. Then eqn (5) becomes:

$$\begin{bmatrix} x_{aM}(100) \\ \vdots \\ x_{aM}(11) \end{bmatrix} = \begin{bmatrix} x_e(95) & \dots & x_e(90) \\ \vdots & & \vdots \\ x_e(6) & \dots & x_e(1) \end{bmatrix} \cdot \begin{bmatrix} g(5) \\ \vdots \\ g(10) \end{bmatrix}$$

Note that a maximum journey time of 10 time units (n=10) means that the first accurate estimation of $x_{aM}(k)$ occurs at k=11.

The unknown parameters g(j), j=m, ... n, are to be estimated from a scheme illustrated in Fig 8. The model output, $x_{aM}(k)$, is compared with the system (i.e. the traffic link) output, $x_a(k)$. A noise term, z(k), is included in the model to represent disturbances such as side-street traffic or vehicles that change lanes into and out of the lane monitored. The error term, e(k), is calculated as:

$$e(k) = x_a(k) - x_{aM}(k)$$

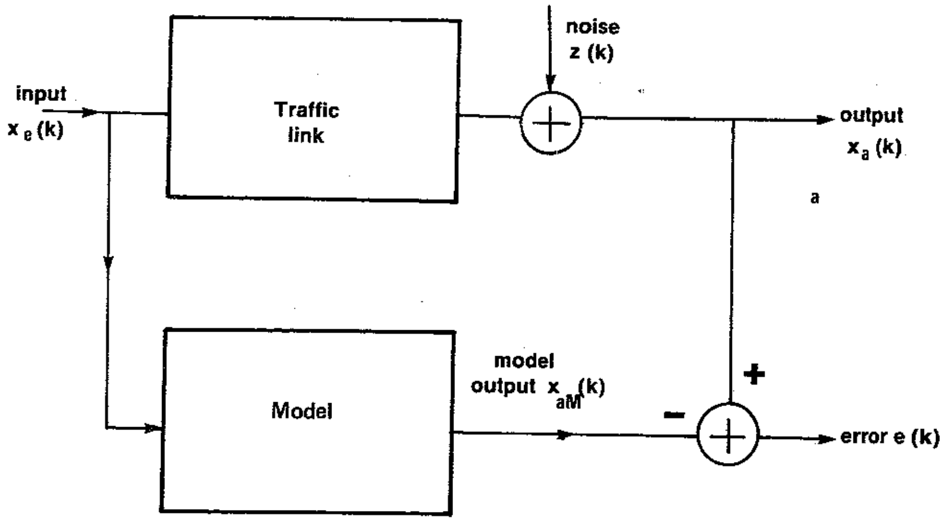

Fig 8 - A parameter estimation method by least squares

The parameter estimation problem can now be expressed by minimising Q, the sum of the squares of the error terms, e(k). In matrix notation,

$$\text{minimise } Q = \underline{e}^t . \underline{e}$$

where $\underline{e}^t$ is the transpose of $\underline{e}$.

$$\text{with } \underline{e} = \underline{x}_a - \underline{x}_{aM}$$

$$\text{or } \underline{e} = \underline{x}_a - \underline{U}.\underline{g} \qquad (9)$$

Equation (9) is generally known as the normal equation (Goodwin and Payne 1977) and the optimal solution is given by:

$$\hat{\underline{g}} = [\,\underline{U}^t . \underline{U}\,]^{-1} . \underline{U}^t . \underline{x}_a \qquad (10)$$

The values calculated from eqn (10) can be negative. Strobel (1977) suggested that a negative g(j) would be of no meaning and should be set to 0. Equation 7 for the probability density function f(j) is then given by:

$$f(j) = \begin{cases} 0 & \text{if } g(j) \leq 0 \\ \dfrac{g(j)}{\sum_j g(j)} & \text{if } g(j) > 0 \end{cases}$$

It should be emphasised that only the input sequence x_e and the output sequence x_a are known and measurable quantities. The noise traffic is not measurable. The power of the least squares (LS) estimation technique is that it gives the best possible solution, in a least squares sense, under a noisy environment.

The authors would also like to suggest that the split coefficient has significant interpretation within the context of ATC. It is an indication of the goodness of signal co-ordination. With proper choice of the offsets, or the start times of green phases of adjacent intersections, vehicles should be able to move in compact platoons within an ATC network. Vehicles in the same platoon should be able to pass through an intersection in one green phase and, if the platoon is compact, they cannot change lanes freely. Thus, high values of the split coefficients in an ATC network indicate that the signal timings are properly tuned to prevailing conditions.

In the analysis below, all solutions were obtained using the subroutine LLBQF in the package IMSL(1980).

Simulated Data

The above formulation was first investigated with the output time series $x_a(k)$ simulated from the input time series $x_e(k)$. The input series was collected from the upstream detector station in the Burwood Highway test site (see Fig 2). It consists of 339 samples with a time resolution (dt) of 10 s. In the simulation, all vehicles travelling from A to B were assumed to arrive at B from A, i.e. the split coefficient h(n)=1. The following journey time distribution was assigned to the vehicles:

j	4	5	6	7	8
g(j)	0	.33	.33	.33	0

In other words, with dt=10 s, m= 5 and n= 7, the expected value of the journey time is 60 s. In matrix notation, the LS formulation is:

$$\begin{bmatrix} e(339) \\ \vdots \\ e(9) \end{bmatrix} = \begin{bmatrix} x_a(339) \\ \vdots \\ x_a(9) \end{bmatrix} - \begin{bmatrix} x_e(335) & \cdots & x_e(331) \\ \vdots & & \vdots \\ x_e(5) & \cdots & x_e(1) \end{bmatrix} \cdot \begin{bmatrix} g(4) \\ \vdots \\ g(8) \end{bmatrix}$$

Some noise traffic was also generated randomly with the noise to signal ratio (N/S) set to 0 and 0.5. The maximum number of vehicles generated as noise was fixed at 5 per 10 s. z(k) was added to the simulated model output $x_{aM}(k)$ at each k. The results are shown in Table VI.

TABLE VI

SIMULATED LEAST SQUARES (LS) RESULTS

	True Values	Simulated Values			
		By Wheelbase		By Flow	
		N/S=0	N/S=0.5	N/S=0	N/S=0.5
g(4)	0.0	0.004	-0.009	0.072	0.117
g(5)	0.333	0.306	0.292	0.230	0.182
g(6)	0.333	0.333	0.332	0.393	0.436
g(7)	0.333	0.330	0.341	0.350	0.434
g(8)	0.0	-0.016	-0.018	-0.061	-0.114
split coeff. h(8)	1.0	0.956	0.938	0.984	1.05
mean journey time(s)	60.0	60.2	60.5	59.8	60.2

The results are encouraging. Under both noiseless (N/S=0) and noisy (N/S=0.5) conditions, the formulation was able to reproduce the right journey time of 60 s and split coefficient of 1. The correct results were obtained using either wheelbase or flow time series. At N/S=0.5, the individual values of the impulse response parameters, g(j)'s, differ from the true values. The solution is still accurate, suggesting that the formulation is robust and not sensitive to noise. The values of g(4) and g(5), which should both be 1/3, were found to be better estimated using wheelbase than using traffic flow. This was anticipated because a wheelbase length should give more information than a count of 1. It is interesting to note that correlation of traffic flow profiles also provides good estimates of the desired parameters. Thus, the original proposal in Strobel(1977) to use traffic counts is an acceptable concept.

Empirical Data

The second phase of the analysis was to use the least squares estimation method to correlate the upstream and downstream data collected from the test site. The input and output sequences were divided into shorter sequences of 15 min each as in Table III. A measurement period of 15 min was arbitrarily chosen. It is long enough to provide a reasonable representative value for that 15 min and provides sufficient data points for LS estimation.

Two sampling intervals (dt) of 1 s and 2 s were used in the analysis to obtain the accuracy required for an expected journey time of about 20 s. For longer journey times, dt = 5 or 10 s would be appropriate. The choice is a trade-off between accuracy and computational efficiency. Ten parameters (g(j)'s) were used in the LS formulation. For dt=1 s, the values m=15 and n=24 were used, i.e. the minimum and maximum journey times were 15 s and 24 s respectively. For clarity of presentation, the results for dt = 1 s, together with the true values, are only shown in Table VII. They are separated into correlation by flow, by wheelbase without trucks and by wheelbase for all vehicles.

TABLE VII

EMPIRICAL LEAST SQUARES (LS) RESULTS

	Time	True Values	Flow (all veh)	W'base (no trucks)	W'base (all veh)
Mean Journey Time (s)	1	18.8	18.6	18.3	19.1
	2	19.3	18.8	19.0	19.4
	3	19.3	19.4	19.4	19.7
	4	18.8	18.9	18.7	19.9
	5	19.6	18.8	18.7	19.2
	6	20.1	18.9	19.3	19.6
	7	20.0	19.3	19.9	20.1
Split Coeff. h(24)	1	0.51	0.60	0.59	0.67
	2	0.67	0.66	0.63	0.75
	3	0.59	0.67	0.64	0.57
	4	0.60	0.73	0.73	0.64
	5	0.62	0.79	0.75	0.73
	6	0.59	0.73	0.68	0.96
	7	0.59	0.64	0.63	0.56

The following observations can be drawn from these results:

(a) The journey times estimated from either traffic flow or wheelbase length agree well with true values. The presence of trucks appears to have affected the split coefficients more than the journey times. The error was most significant in period 6 when the true value of h(n) was 0.59 in comparison with h(n)=0.96 estimated with trucks included. With trucks excluded, h(n)=0.68 and was a much closer estimate.

(b) The average link journey time increased as the peak flow built up at around periods 5 and 6 (about 4.30 p.m.). This was the case at the test site.

(c) The empirical results confirm that the observation made from the simulated analysis that traffic flow is indeed a useful quantity for parameter estimation. Traffic flow also has the advantage that it can be collected using only one axle or loop detector for data collection.

(d) The benefit of utilising the extra information inherent in a wheelbase sequence in a least squares framework has yet to be ascertained. This aspect will constitute an important area of research.

FUTURE WORK

The use of parameter estimation methods for extracting journey time and O-D information from time series data is a new area of research. Limited publications in this area include the work of Strobel (1977) and Cremer and Keller (1981, 1984). In their reported work, Cremer and Keller attempted to obtain an O-D trip matrix using a sampling interval of a few minutes. Within the context of ATC, dt should be less than 10 s. A small value of dt would also better utilise the extra information inherent in a wheelbase sequence. The authors are satisfied with this initial attempt in applying the least squares technique, and the wheelbase matching method, for on-line evaluation of ATC. They are confident that these methods can be further developed into tools suitable for daily operation. Future research would include the following:

(a) More field studies would be organised for links or routes of longer lengths. The Burwood Highway site could be used again but with detector station B moved away from A to provide link distances of, say, 700 m and 1 km. More complex sites should be investigated. This will allow the study of the left-over queue that belongs to the tail of a platoon. Multivariate anlaysis, i.e. more than one input/output time series, can be easily incorporated within the framework of eqn (5). This is particularly useful for calculating the O-D trip matrix. The LS estimation technique is in fact an alternative to the entropy maximisation method commonly employed (see, e.g. Bell 1983).

(b) The only pre-processing adopted in both the cross-correlation and least squares (LS) analysis was the subtraction of the mean value from a given time series. More sophisticated pre-processing, called pre-whitening (Box and Jenkins 1976), can be employed to improve the accuracy of estimation. As already mentioned, the time series data obtained from detectors in an ATC network is expected to contain a cyclic or seasonal component. This component corresponds to the cycle length adopted in a signal controlled area. More accurate results can be obtained if the seasonal trend can be isolated. In frequency domain, this is interpreted as the filtering of unwanted signals.

(c) The least squares technique can be converted into a recursive algorithm that allows new data to be included and old data discarded continuously. Recursive algorithms are computationally more efficient. They will enable a dynamic response to changes in prevailing traffic conditions. Recursive least squares techniques are commonly employed in real-time applications (Goodwin and Payne 1977). It is quite feasible to implement the LS estimation as recursive algorithms in a microprocessor traffic controller.

CONCLUSIONS

AVI without identifying individual vehicles is a difficult problem. This paper investigates three methods for the estimation of link journey times in an ATC system by identifying sequences of vehicles. The first method relies on the matching of wheelbase sequences and is suitable for estimating journey times cycle by cycle. The other two methods, cross-correlation and least squares estimation, are suitable for observation periods of about 15 min. The presence of trucks appeared to have affected the use of wheelbase sequences in these two methods, especially the cross-correlation. Both wheelbase and traffic flow time series were investigated using the least squares estimation method. Intuitively, wheelbases provide more information than traffic counts; but the results obtained indicate further research is necessary to utilise this extra information. Least squares estimation using traffic counts was found to produce satisfactory results and was not sensitive to noise such as side-street traffic. It also provides information on the goodness of signal co-ordination, and can be extended as a multivariate analysis problem to calculate an origin-destination trip matrix. An important area of future research is the refinement of the least squares method into a recursive algorithm suitable for implementation in a local traffic signal controller.

REFERENCES

BELL, M.G.H. (1983). The estimation of an origin-destination matrix from traffic counts. Transp. Sci. 17(2), pp.198-217.

BOX, G.E.P. and JENKINS, G.M. (1976). Time Series Analysis: Forecasting and Control. 2nd ed. (Holden-day: San Francisco).

CATLING, I. and TURNER, J.D. (1984). Automatic data collection in Hong Kong. Int. Conf. on Road Traffic Data Collection, December, London. Inst. of Elec. Eng. Conf. Pub. No. 242, pp.83-86.

CREMER, M. and KELLER, H. (1981). Dynamic identification of flows from traffic counts at complex intersections. Proc. 8th Int. Sym. on Transp. and Traffic Theory, Toronto, pp.199-209.

CREMER, M. and KELLER, H. (1984). A systems dynamics approach to the estimation of entry and exit O-D flows. Proc. 9th Int. Sym. on Transp. and Traffic Theory, Hamburg, pp.431-450.

DAWSON, J.A.L. (1983). Electronic road pricing in Hong Kong: the pilot stage. Traff. Eng. Control 24(8), pp.372-374.

ELECTROMATIC (1980). Passive Identification System (5 pages).

FRASER, P.J. (1981). The ARRB vehicle detector data acquisition system (VDDAS). Australian Road Research Board. Technical Manual, ATM No. 12.

GAZIS, D.C. and FOOTE, R.S. (1969). Surveillance and control of tunnel traffic by an on-line digital computer. Transp. Sci. 3(2), pp.255-275.

GOODWIN, G.C. and PAYNE, R.L. (1977). Dynamic System Identification: Experimental Design and Data Analysis. (Academic: New York).

IMSL (1980). International Mathematical and Statistical Library Inc., Reference Manual. (IMSL: Texas).

KENYON, M. (1983). A probabilistic study of time delay measurement by cross-correlation estimation. M. Eng. Sc. Thesis, Monash Univ.

LUK, J.Y.K. (1983). Vehicle identification and the evaluation of area traffic control systems. Australian Road Research Board. Internal Report AIR 395-3.

LUK, J.Y.K. (1985). Report on an O.E.C.D Seminar in Tokyo and electronic road pricing in Hong Kong. Australian Road Research Report. Internal Report AIR 395-4.

LUK, J.Y.K., SIMS, A.G. and LOWRIE, P.R. (1983). The Parramatta Experiment - evaluating four methods of area traffic control. Australian Road Research Board. Research Report, ARR No. 132.

MELBOURNE METROPOLITAN TRAMWAYS BOARD (1982). Manufacture, supply and delivery of an automatic vehicle monitoring system. Tender schedule. Contract No. 3500.

NG, M.J.T. and LUK, J.Y.K. (1983). Frequency domain analysis of the TRANSYT vehicle dispersion model. Journal of Electrical and Electronic Engineering, Australia. 3(4), pp.304-309.

RICHARDSON, A.J., OGDEN, K.W., STEVENSON, J.McL. and KINNEAR, R.L. (1978). The evaluation of bus priority traffic signals. Aust. Rd Res. 8(4), pp.35-47.

RICHARDSON, A.J. and OGDEN, K.W. (1979). Evaluation of active bus-priority signals. Transp. Res. Rec. 718, pp. 5-11.

SIMS, A.G. and DOBINSON, K.W. (1980). The Sydney Co-ordinated Adaptive Traffic (SCAT) system philosophy and benefits. IEEE Trans. Veh. Technol. VT-29(2), pp.130-136.

SIN, F.Y.C. (1984). Selective tram detection system. Proc. 12th ARRB Conf. 12(4), pp.150-159.

SKOMAL, E.N. (1981). Automatic Vehicle Locating Systems. (Van Nostrand Reinhold: New York).

STROBEL, H. (1977). Traffic control systems analysis by means of dynamic state and input-output models. Intern. Inst. for Applied Systems Analysis. Research Report RR-77-12.

TOMKEWITSCH, R. (1984). Communication between information beacons and vehicles provided with infrared equipment. Proc. O.E.C.D. Seminar on Microelectronics for Road and Traffic Management. Tokyo, October, pp.192-201.

WATSON, P.L. and HOLLAND, E.P. (1978). Relieving traffic congestion: the Singapore Area License Scheme. World Bank Staff Working Paper No. 281

YUMOTO, N., IHARA, H., TABE, T. and NANIWADA, M. (1979). Outline of the Comprehensive Automobile Traffic Control pilot test system. Transp. Res. Rec. 737, pp.113-121.