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ALGORITHMS FOR THE COMPUTER CONTROL OF URBAN TRAFFIC

by J. S. Baras and W. S. Levine

Abstract

Recent developments in computer technology have made substantial computational capability, in the form of mini- and micro-computers, available at modest prices. This, coupled with the available traffic sensors, controllable traffic signals and communications, makes the computer control of traffic feasible in many urban areas today. Many such systems are either operating or are being planned.

Software for today's hardware environment can be oriented toward several, or many, small machines each of which controls a small local area. Alternatively, the software can do more pre-processing of data in a small machine located near the detector thereby reducing communication costs.

This paper describes a set of filtering, prediction and control algorithms that are primarily intended for traffic responsive control of networks. A way to partition the network algorithms among a collection of microprocessors is proposed. Because of the way in which the control computations can be partitioned, the algorithms will also work well for isolated intersections.

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1. Introduction

Recent developments in computer technology have made substantial computational capability, in the form of mini- and micro-computers, available at modest prices. This, coupled with the available traffic sensors, controllable traffic signals and communications, makes the use of computers to control traffic economically feasible in many urban areas today. As a result, many computer controlled systems are either operating or being planned.

Generally, the traffic control systems for networks operate in an open-loop or time of day mode. Some systems do utilize detector data to decide when to switch from one stored timing pattern to another. However, even though isolated intersections are frequently controlled in a fully traffic responsive manner, it is very unusual to find a fully traffic responsive network control system. Moreover, several attempts to develop and test fully traffic responsive network controls resulted in worse performance than that achieved on the same network by time of day control [1], [2].

The intent of the research summarized here was to design traffic responsive control algorithms that would perform better than the best open loop controls.

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The approach taken consisted of three steps. First, a mathematical model was developed which, hopefully, captures the statistical relationship between detector data and the flow of traffic in the network. Second, optimal filters and predictors of queues at traffic signals and flow of platoons in the network were developed. These filters/predictors were based on the previously developed models and, fortunately, could be realized in a microprocessor. Finally, control algorithms were designed which utilized the data from the filters/predictors. All of the filters/predictors and most of the control algorithms have been tested using the UTCS-1 traffic simulation [3], [4] developed for FHWA.

The following section of this paper describes the mathematical model. Then, in the third section the filters/predictors based on the model are described. It is believed that these filters/predictors can be used to improve controls at isolated intersections as well as for network control. Thus, in the fourth section, some results on the control of isolated intersections are given. The fifth section contains results on the network control problem. Finally, the paper concludes with some suggestions for further research and development.

2. Mathematical Model

The modern approach to control system design begins with the development of a mathematical model. In this case, the model was partly determined by the initial conjecture that a traffic responsive control system needed to respond to detector data with a minimal delay (< 5 minutes). This implied that long time averages of detector data could not be used. The advantage of a long time average is that the averaged data can be modeled, with reasonable accuracy, by a Gaussian stochastic process. Over short intervals, however, detector data is not Gaussian. A realistic model must be a point process. That is, a stochastic time signal in which the time of occurrence of an event is significant, not the size of the event. (A Poisson process is the simplest example of a point process). Thus, the first problem was to develop a mathematical model for the relation between the detector data (point process) and relevant measures of traffic flow on a network.

The two best known optimization routines for determining pre-timed signal patterns on traffic networks, TRANSYT [5] and SIGOP [6], are based on the flow of platoons on the network and the size of queues at traffic signals. Thus, we decided to try to model the statistical relationship between detector data and queues and platoons on the network. This insured that our model would be, at least approximately, consistent with TRANSYT and SIGOP. However, our model needed to be different from SIGOP and TRANSYT in at least one respect. Our model had to include, and account for in terms of queues and platoons, detector data.

The next step in the development of our model was to try to decompose the network into manageable pieces. This was accomplished by making the following approximations:

(1) The queue at a traffic signal depends primarily on the traffic signal, the upstream traffic signal and the volume of traffic on the link.

(2) The platoon crossing a detector depends primarily on the queue that existed just previously at the upstream signal and the upstream signal.

These approximations are obviously not valid for a saturated network or for long (>5 minutes) predictions. However, we are primarily interested in short predictions. In addition we believe that significant improvement in traffic control via responsive methods is possible primarily in the undersaturated case.

The advantage of the above approximations is that the mathematical model of traffic flow on a network reduces to three components

(1) the queue at each arm of an intersection

(2) the passage of each platoon over each detector in the network

(3) the coordination of the above models to determine overall network behavior.

2.1 Queue Model

The first component, the queue at each arm of an intersection, will be described first since it is independent of the other two. The simplest practical queueing situation is the intersection of two one-way, single-lane streets. Consider the situation illustrated in Fig. 1. Assume, for simplicity, that the light operates on a simple known red-green cycle (no amber), that there is only one detector, and that the detector is located N car lengths from the stop line.

The observed signal from the detector will be denoted by $n^a(t)$,

$$n^a(t)=\begin{cases} 0, & \text{if no vehicle is over the detector} \\ 1, & \text{if a vehicle is over the detector} \end{cases} \tag{2.1}$$

In practice, time is discretized with a small enough discretization interval (1/32 second in UTCS) for each vehicle to be over the detector for several samples. For simplicity, it is assumed here that the data are sampled so that each vehicle produces exactly one pulse (one 1).

Intuitively, one can regard $n^a(t)$, for each t, as the outcome of a coin toss where 1 corresponds to heads. In the traffic case, for such an intuitive picture to make sense, the coin must be "unfair" in the sense that λ = Probability of getting heads ($n^a(t) = 1$) is not 1/2. Furthermore, $\Pr[n_a(t) = 1]$ depends on time and on various other aspects of the traffic flow on the network. In our model, we assume that $\Pr[n_a(t) = 1]$ depends on the size of the queue at the signal, the timing of the signal immediately upstream, the signal at the intersection and the traffic volume on the link. Thus, let

$$\lambda(k,t) = \Pr[n^a(t) = 1 \text{ given that queue length is k and the time is t}] \tag{2.2}$$

$$z(t) = \text{queue length at time t} . \tag{2.3}$$

Notice that, since $n^a(t) = 1$ means that a vehicle just crossed the detector, $\lambda(k,t)$ has the dimensions of volume (vehicles/second) crossing the detector.

We assume

$$\lambda(k,t) = \begin{cases} \lambda_r & \text{when upstream signal is red and } k < N \\ \lambda_g & \text{when upstream signal is green and } k < N \end{cases} \tag{2.4}$$

$$\lambda(N,t) = 0 \tag{2.5}$$

The reasoning is as follows:

(1) When the queue contains N vehicles, no more vehicles can cross the detector so the arrival volume equals 0.

(2) When the upstream signal is green, after a short delay, the arrival volume at the detector is determined by the straight through flow on the street.

(3) When the upstream signal is red, after a short delay, the arrival volume at the detector is determined primarily by turning traffic at the upstream intersection.

Equation (2.4) can be viewed as a two time period approximation to the plots of traffic flow vs time (for one cycle) that are fundamental in the TRANSYT model.

Similarly, if one imagines a detector at the stop-line, one obtains an unobserved point process $n^d(t)$ at the stop line.

$$n^d(t) = \begin{cases} 1 & \text{if a vehicle departs} \\ 0 & \text{otherwise} \end{cases} \tag{2.6}$$

We assume $n^d(t)$ (more precisely, $Pr[n^d(t) = 1]$) is determined by the queue and the traffic signal shown in Fig. 1. That is,

$$\mu(k,t) = Pr[1 \text{ departure given } k \text{ vehicles in queue at time } t] \tag{2.7}$$

$$\mu(k,t) = \begin{cases} \mu & \text{when traffic signal is green and } k > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.8}$$

Note that μ is approximately the saturation flow at the intersection (in veh./sec).

At this point, the model of the single arm of the intersection is complete.

To see this, suppose there are i vehicles in the queue at time t. We want to calculate the probability that there are j vehicles in the queue at time t + 1 and the probability that $n^a(t) = 1$.

$$\Pr[n^a(t) = 1 \text{ given i vehicles in queue}] = \begin{cases} \lambda \,, & i < N \\ 0 \,, & i = N \end{cases} \tag{2.9}$$

$$\Pr[z(t+1) = j \mid z(t) = i] = \begin{cases} 0 \,, & j < i-1,\ j > i+1 \\ \lambda(i,t)\,\mu(i,t) + (1-\lambda(i,t))(1-\mu(i,t)), & i=j \\ \lambda(i,t)(1-\mu(i,t)) & ,j=i+1 \\ \mu(i,t)(1-\lambda(i,t)) & ,j=i-1 \end{cases} \tag{2.10}$$

The model is developed in much more detail in [7], [8] and [9]. The above model has been described in terms of the simplest possible intersection. However, it can be applied to much more complex intersections by means of some small adjustments. In our report [7] we describe the derivation of the model, derive two other more elaborate models and give a description of the technique so that other similar models can be constructed by the user.

Note that there are some nice aspects to the above model. First, the control variable is $\mu(k,t)$. Second, the model depends on only three parameters. To be practically useful a mathematical model has to depend on a minimum number of parameters and, since these parameters have to be determined by estimation or observation, the model's behavior cannot depend too critically on the parameter values. Our tests, reported in [7] show the model is insensitive to the parameters. We will describe methods to estimate these parameters subsequently.

2.2 Platoon Model

We will describe the platoon passage model in terms of the simple situation illustrated in Fig. 1. Suppose that, some short time previously, the signal just upstream of the figure has turned green. This releases the queue at the signal which then flows, as a platoon, over the detector in Fig. 1. We assume that the arrival of the lead vehicle in the platoon is easily predictable and that the fundamental problem is to estimate the passage of the last vehicle in the platoon. While the platoon is crossing the detector, we assume that time headways between successive vehicles (time between successive 1's of $n^a(t)$) satisfy a lognormal distribution

$$p_f(h) = \begin{cases} \dfrac{1}{\sigma h\sqrt{2\pi}} \exp \dfrac{(\ell n h - \alpha)^2}{2\sigma^2} & , h \geq 0 \\ 0 & , h < 0 \end{cases} \tag{2.11}$$

Once the platoon has past we assume free-flowing traffic satisfying a displaced exponential distribution.

$$p_{nf}(h) = \begin{cases} \beta \exp(-(h-\tau)\beta) & , h \geq \tau \\ 0 & , < \tau \end{cases} \tag{2.12}$$

We assume that successive headways are independent. Thus, headway statistics at the detector are completely described by the probability density of headway

$$p(h) = \psi(t)\, p_f(h) + (1-\psi(t))\, p_{nf}(h) \tag{2.13}$$

where $\psi(t)$ denotes the switch from following to non-following headways and is determined by the upstream traffic signal.

This actually completes the formulation of the platoon passage model. Again, more details can be found in [7], [9], [10], [11]. There, variations of the model which apply to freeways are also described. Furthermore, the model is closely related to other models for platoon flow (see [7] and [10] for references). Finally, this model depends on only four parameters α,σ,β,τ. It is known, and demonstrated in [10], that the results are fairly insensitive to the parameter values.

2.3 Coordination

Coordination of these local models is achieved in the following manner. The model for the queue at an arm of an intersection depends only on λ_r, λ_g, μ and the time the upstream traffic signal switches from red to green. The only parameter that is not localized at the intersection is the switching time of the upstream signal. Thus, each intersection queue model is coordinated with its upstream neighbor via the switch time of the upstream signal.

The start of passage of each platoon over the detector is also given primarily by the switch of the upstream signal. The end of the platoon is related to the queue that existed just previously at the upstream signal. In our report [7] we describe in detail how the platoon passage estimator depends on the upstream queue estimate and how the platoon passage estimator can be used to improve, a posteriori, the queue estimate.

Another way to view our network model, and hence control strategy, is in terms of two time scales. The network coordination (the slow time scale) is modeled by a TRANSYT type model (our gross model is cruder than TRANSYT). At each intersection and at each detector a much more detailed model of queueing and platoon passage is used. These detailed models are meant to operate at a fast time scale and to correct for local deviations from the average behavior.

3. Filters/Predictors

Since the model of traffic flow on the network decomposes into a collection of single queue and single platoon models the filtering and prediction problem decomposes in the same manner. We emphasize that the coordination between these individual models, or equivalently the network aspect of the model, is provided primarily by the traffic signals.

3.1 Queue Filter/Predictor

The queue filter/predictor is based on the model described in Section 2.1. We give a block diagram for the mathematically optimal filter/predictor in Fig. 2. Note that,

(1) $n^a(t)$ is the detector signal as before,

(2) $\hat{\underline{x}}(t|t)$ is equivalent to the filtered estimate of queue, see below,

(3) $\hat{\underline{x}}(t+1|t)$ is equivalent to the one step predicted estimate of queue.

In fact,

$$\hat{\underline{x}}^T(t|t) = [\hat{x}_o(t|t)\ \hat{x}_1(t|t)\ \ldots\ldots\ \hat{x}_N(t|t)] \tag{3.1}$$

$$\hat{x}_i(t|t) = \Pr\left[\, i \text{ vehicles in queue at time } t|n^a(t)\,\right] \tag{3.2}$$

and similarly for $\hat{\underline{x}}(t+1|t)$. Note that $\underline{M}(t)$ and $\underline{Q}(t)$ are explicit functions of λ_r, λ_g and μ. Again, see [7], [8] or [9] for details as well as other filters/predictors. The essential point is that these calculations can be done in a micro-processor as can be seen from Fig. 2.

This estimator was tested using the UTCS-1 simulation model under varying traffic conditions. These tests are reported in great detail in [7] and in lesser detail in [8] and [9]. The performance of the estimator in all of the tests was excellent. One especially relevant series of tests is summarized in Tables 1 and 2. There, ASCOT [12], [13], a queue estimator in current use is compared with our estimator using data from UTCS-1. As can be seen, our estimator is generally better.

3.2 Platoon Passage Filter/Predictor

The platoon passage estimators are based on the model described in Section 2.2. In this case, we have developed several possible estimators. Again, detailed algorithms are given in [7], [9], [10] and [11]. These algorithms are simple enough to code and execute in a microprocessor.

Two of these algorithms, the Threshold and Maximum Jump (MJ) Estimators, have been tested using the UTCS-1 data. The details can be found in [7]. Tables 3 and 4 summarize these results. Note that the large apparent errors in Table 3 are the result of the queue from an intersection further upstream catching the platoon whose length is being estimated. Thus, the estimators are accurate estimators of platoon sizes and passage time. The tables show the platoon estimator being used to estimate the queue at the signal upstream from the detector. The results show good performance for long links and poor performance (because of the above described interference from further upstream) for short links.

We have since developed better estimators of platoon size. Some test results, based on simulation of our model, are shown in Table 5. The MJ Est is the Maximum Jump from Tables 3 and 4 and gives a basis for comparison. The details of the MAP and ML estimator can be found in [11].

3.3 Network Considerations

The filters/predictors described above are very effective for prediction within one cycle (approximately one minute). When used to predict over longer periods they reduce to an approximation to the TRANSYT model. Since the overall network control requires longer prediction periods than one minute, the network aspects of prediction would be handled, in our methodology, by TRANSYT or SIGOP.

4. Control of Isolated Intersections

The control of isolated intersections is greatly simplified by the absence of coordination. Thus, our simple queueing and platooning models apply with no other data required. Given a simple intersection, one can apply the queue model to each arm independently. This ignores some left-turn interference but is a reasonable approximation that can be easily corrected. Based on this model one can prove that the mathematically optimal control operates in two components:

1) Compute $\hat{\underline{x}}(t+1|t)$ from our filter/predictor.

2) The optimal control depends only on $\hat{\underline{x}}(t+1|t)$. However, even after the above separation of estimation and control, the optimal control requires too much computation to be practical.

Instead, we evaluated several sub-optimal controls in which our queue estimator was used as the input to previously proposed intersection control algorithms. Three controllers were tested against a single intersection simulated via the UTCS-1 simulation. A pure open-loop control using Webster's method provided a benchmark. A control due to Darroch, Newell and Morris [14] and one due to Michalopoulos and Stephanopoulos [15] were tested in versions incorporating our queue estimators. Both closed-loop schemes performed significantly better than the open-loop scheme in moderate traffic. The open-loop scheme, as might be expected since our models break down for heavy traffic, was better in heavy traffic. These results will be reported in detail in [16].

5. Control of Networks

The strategy we are proposing for network control would operate in two levels. The overall network control would be based on pre-stored timing plans computed via TRANSYT, SIGOP or a similar procedure. "Small" adjustments to this overall control would be made at each intersection. These adjustments would be based on our queue and platoon estimates. For example, the local controller might introduce a ten second shift in offset to allow a queue to clear the intersection before the platoon from upstream arrives. Or, the local controller could change the split for one cycle to take advantage of an opportunity to service the side street during momentarily light volume on the main street.

Such a scheme could be implemented with a microprocessor at each intersection or small group of intersections. A central processor could communicate neighboring cycle, split and offset to the local controller. The local controller could make small adjustments to these based on its local detector data. The local processor would transmit its queue size estimates and platoon passage and size estimates to the central processor. Note that communication could be once per cycle or less. The data from local controllers would be used by the central controller to switch from one timing plan to the next and to evaluate overall system performance.

We have not yet evaluated the performance of such a controller. More details will be found in [16].

6. Directions for Further Research

The algorithms proposed here are determined by a small parameter set on each link containing a detector. Generally, practical control techniques depend on similar small parameter sets. It is expensive and time consuming to obtain estimates of these parameters via traffic surveys. Frequently, the parameters change shortly after the survey is completed. Similar comments can be made about performance evaluation. In our report [7] we outline a procedure whereby detector data might be used to estimate these parameters. This might be much less expensive than traffic surveys and could be performed much more frequently.

The basic idea is that the λ's,μ,σ,β,α all change "slowly" enough to be estimated from detector data. Further research is required to determine if such parameter estimators converge quickly enough to be useful and to determine if the required storage and computation is feasible. We mention this research because we see it as especially significant. A number of other suggestions can be found in [7] and [16].

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Figure Captions

Figure 1 Detector Location

Figure 2 Block Diagram of Optimal Filter/Predictor

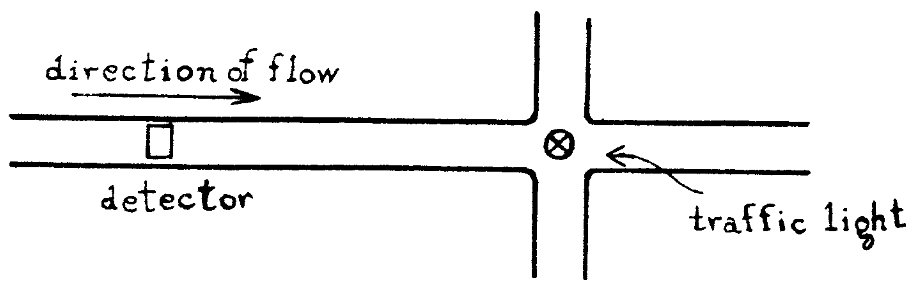

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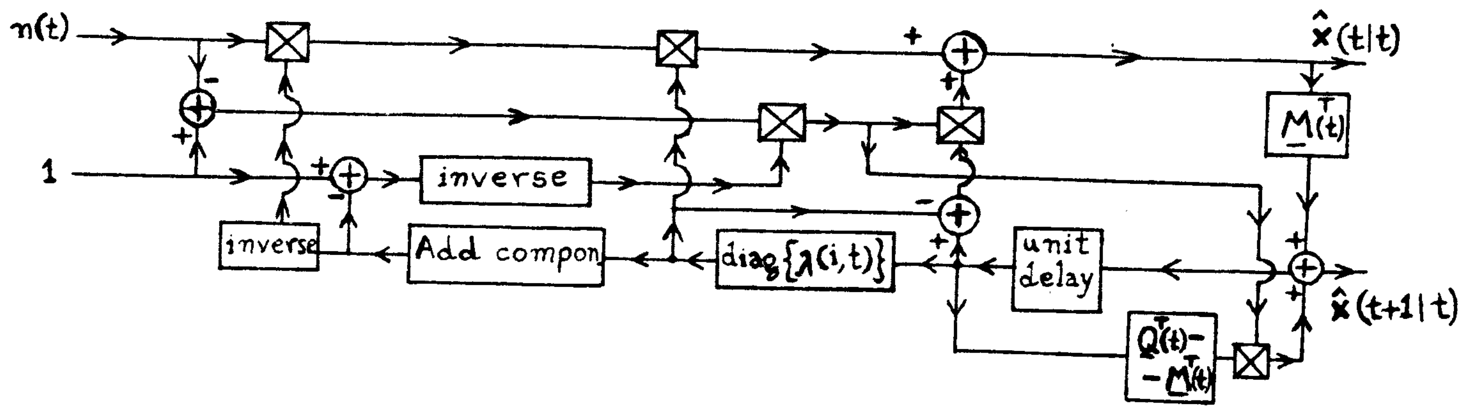
Fig 1



n(t)
1
inverse
inverse
Add compon
diag{λ(i,t)}
unit delay
$\underline{Q}^T(t) - \underline{M}^T(t)$
$\underline{M}^T(t)$
$\hat{x}(t|t)$
$\hat{x}(t+1|t)$

Fig 8

Time	Actual Queue	ASCOT Estimate	F/P Estimate
80	2	3	2.7
160	2	2	2
240	5	5	5
320	5	7	4.5
400	5	7	3.8

Table 1 Comparison of ASCOT with F/P , Moderate Traffic

Time	Actual Queue	ASCOT Estimate	F/P Estimate
80	8	3	5.8
160	9	7	9
240	10	7	9.5
320	10	12	9.5
400	7	7	9.5

Table 2 Comparison of ASCOT with F/P, Heavy Traffic

Cycle Number	Threshold Estimate	Maximum Jump Estimate	Actual Queue
1	11	11	2
2	3	2	2
3	3	3	3
4	10	10	1
5	0	11	1
6	3	3	2

Table 3 Performance of Platoon Estimators , Short Links

Cycle Number	Threshold Estimate	Maximum Jump Estimate	Actual Queue
1	6	7	6
2	6	8	8
3	7	7	7
4	7	7	7
5	9	9	9
6	1	6	7

Table 4 Performance of Platoon Estimators , Long Links

SEQ NUMBER	MJ EST	MAP EST	ML EST	ACTUAL
0	6	4	4	4
1	5	5	5	5
2	6	6	6	6
3	10	10	10	10
4	6	6	6	6
5	4	4	4	3
6	6	6	6	5
7	3	3	3	3
8	13	13	13	13
9	2	2	2	2
10	7	7	7	7
11	10	10	10	8
12	9	9	9	9
13	5	5	5	5
14	1	6	6	6
15	7	7	7	7
16	1	2	2	2
17	11	11	11	9
18	3	3	3	3
19	13	13	13	9

Table 5 Performance of Improved Platoon Estimators