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A methodology for traffic state estimation and signal control utilizing high wireless device penetration

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Abstract This paper presents a methodology for fusing data from multiple sensors, including wireless devices, to make an estimation of the state of an urban traffic network. An extended Kalman filter is employed along with a state evolution model to make estimates of the state in a discretized network. Results are presented from simulation tests of signal controllers on a network with three signalized junctions. Two signal control methods are tested: SCOOT and a machine learning junction control algorithm that employs the discretized state structure described in this paper. These tests represent lower and upper performance benchmarks and present a significant difference. The tests also demonstrate a framework for the future evaluation of the proposed methodology.

Keywords: WiFi, wireless, traffic control, signal control, Kalman filter, neural network, machine learning.

Introduction

The number of wireless devices in the transport network is growing rapidly. This includes smart-phones carried by drivers and passengers, in-car blue-tooth systems (for example in the radio) and, increasingly in-car WiFi. Chrysler, BMW and Toyota are all currently developing and/or marketing in car WiFi systems for information, entertainment and ITS (Intelligent Transportation Systems) applications [1]. In Europe three major studies have recently examined the benefits of vehicle to infrastructure (V2I) and vehicle to vehicle (V2V) WiFi communications [2,3,4]. Furthermore common European protocols have been set for this type of communication (IEEE 802.11p).

It is clear that the future trend is towards a large number of different types of wireless devices in the road traffic network. The data that may be available from these wireless devices carries valuable information that can be exploited by Urban Traffic Control (UTC) systems. The challenge becomes to combine these data sources and existing traffic data sources (e.g. inductive loops [5], microwave detectors [6], cameras [7]) to estimate a ***single coherent image*** of the state of the network.

The potential value of wireless device data in UTC has been investigated by simulating prototype junction systems that employ simulated wireless data in their control algorithms [8,9,10]. This research indicates that signal controllers that employ wireless data can significantly outperform existing control systems (e.g. MOVA [11]) both in terms of delay and equitability. In this case the variance of the distribution of journey times across the junction is taken as a measure of equitability. In particular [9] and [10] show that the fidelity of wireless data supports the use of *machine learning* signal control algorithms, which exhibit high performance.

This paper presents a methodology for estimating a single coherent image of the state of the network that can support machine learning algorithms for urban signalized junction control. The proposed methodology discretizes the road network into small areas at the lane level. Metrics defining the state of the network (e.g. average speed $\bar{V}$, number of vehicles N) are associated with each area and estimated from multiple information sources using an Extended Kalman Filter (EKF).

Simulation test results are presented for two baseline scenarios. One where perfect data are employed along with machine learning control algorithms to control a junction and another where the SCOOT algorithm [12], using inductive loops, is used to control the same junction.

Methodology

The UTC systems described above all use dedicated sensors, which collect *census* data, that is vehicles are detected passing a specific point in space. Wireless device technology *can* be used to collect census data (e.g. with Bluetooth detectors at the roadside), however it can also be used to collect *probe* data, that is tracking the position and speed of individual vehicles.

Trying to combine multiple independent sources of wireless and non-wireless data, which are measuring different things in different ways, can present some challenges. For example, not all of the data sources are available all of the time (latency); data from different sources may be contradictory; some vehicles may contain multiple wireless devices, some none (penetration).

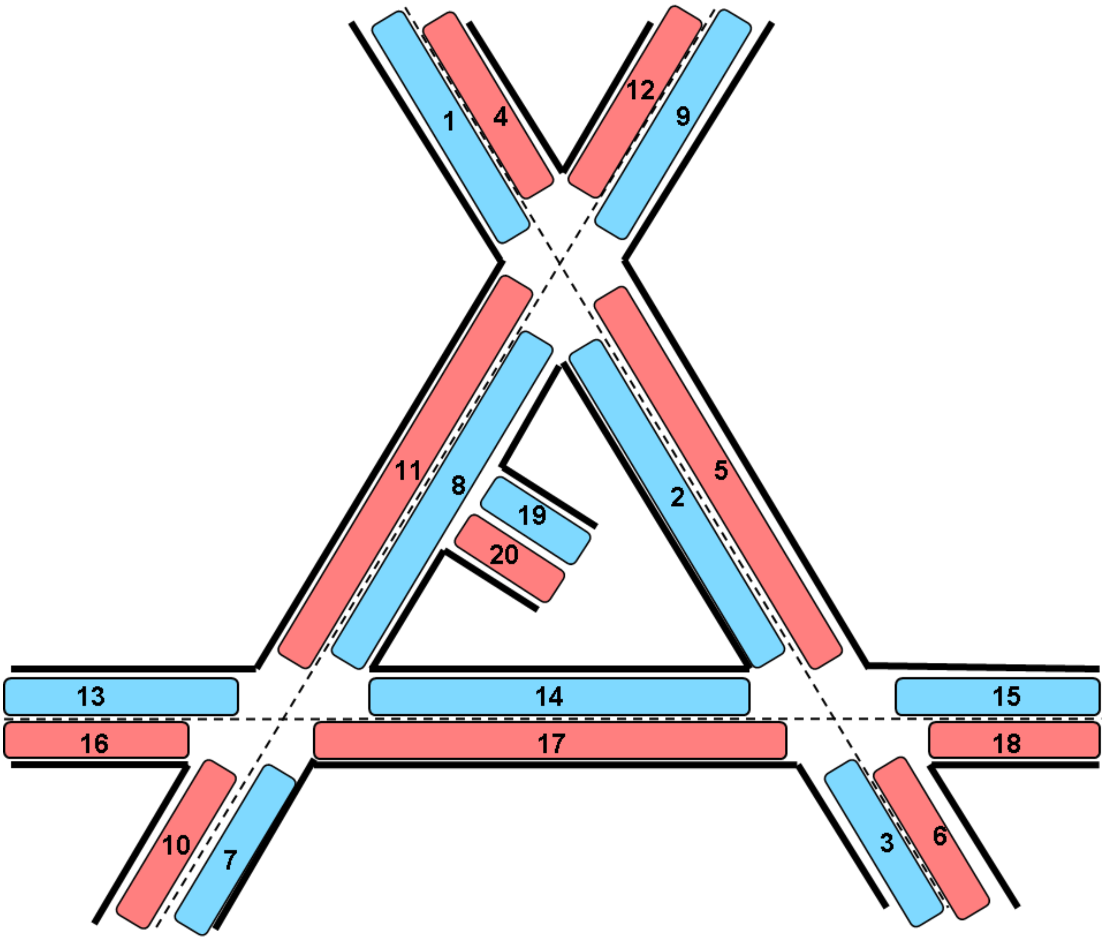

Figure 1 – A four junction network with three signalized junctions (the corners of the triangle) is discretised into areas (numbered) to define the network *state*.

The proposed methodology to meet these challenges is to employ an Extended Kalman Filter (EKF) [13] as described in this section.

Definition of State

Within the EKF framework we assume that no single source of information is providing the truth of the state on the road but is instead providing us with *evidence* of a state, which must be defined. To define the *state* we discretize the network up into small areas, an example is shown in Figure 1. Each area has one or more *metrics* associated with it. In the example presented here we assume two metrics: *mean vehicle speed*, averaged across all vehicles in the area at time t $(\overline{V}_t)$ and *number of vehicles* in the area at time (N_t). The size/granularity of areas is something which can be set up in the design of the network state and tuned to provide the required level of complexity in information.

The EKF framework employs a *state evolution model* to make a prediction of the state in each area by dynamically modelling how these states change with time. The prediction is then used estimate the sensor measurements that will be collected via the *sensor model.* The EKF equations [13] use the difference between these predicted sensor measurements and the actual recorded measurements to estimate the true state in each area. Examples of a simple state evolution model and sensor model are given below.

State Evolution Model

When dynamically assessing the state of the network it is possible to make reasonable predictions of how the state will evolve over the very short term, even in the absence of any information from sensors. This can be useful, especially during short periods of high sensor latency. An example of a simple state evolution model is presented below.

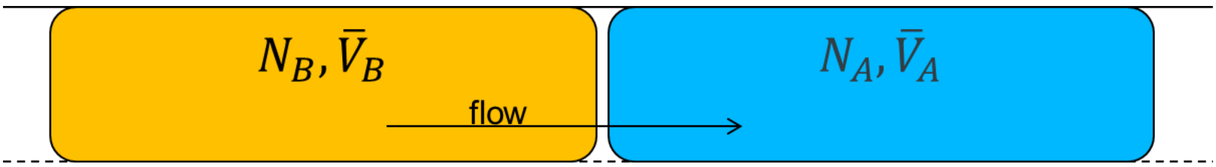

Figure 2 – State evolution model predict the flow of vehicles between neighbouring areas.

Each area in the network is considered individually along with its upstream neighbour (Figure 2). The out-flow of an area at time $t (Q_t)$ is estimated from $\bar{V}_t$ and N_t within the area using (1), for the special case where end of the area corresponds with a junction stop line and the light is currently red, where $Q_t = 0$ (1).

$$Q_t = \begin{cases} 0 & at\ a\ red\ light \\ \dfrac{N_t\ \bar{V}_t}{l} & otherwise \end{cases} \tag{1}$$

Where l is the total length of all lanes in the area.

The model estimates the state in area A at time $t+1$ as

$$N_{A,t+1} = N_{A,t} + Q_{B,t}\delta t - Q_{A,t}\delta t \tag{2}$$

$$\boldsymbol{\bar{V}_{A,t+1}} = \boldsymbol{\bar{V}_{A,t}} \tag{3}$$

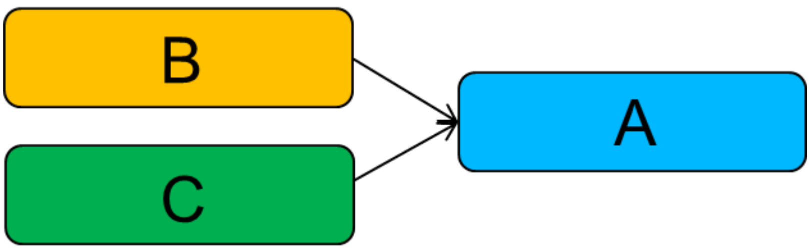

Figure 3 – State evolution model – multiple upstream neighbours are possible e.g. at junctions

Where δt is the time step between t and $t+1$. In the event that area A has more than one upstream neighbour (Figure 3), for example, at a junction, then the model is adjusted as in equation (4).

$$N_{A,t+1} = N_{A,t} + Q_{B,t}\delta t + Q_{C,t}\delta t - Q_{A,t}\delta t \quad (4)$$

Sensor Model

The goal of the sensor model is to estimate the sensor signals that will be received given the predicted state. The specific sensor model employed depends on how many sensors, which collect census data are in the area of interest and how many *types* of wireless probe sensors are currently in the network. In general for a census sensor C_1, The expected number of counts registered on the sensor for time interval δt. Is modelled as in (9), where the superscript (-) indicates the value predicted by the state evolution model.

$$N^{C_1} = \frac{N_{A,t+1}^{-}\bar{V}_{A,t+1}^{-}\delta t}{l} \quad (9)$$

For a wireless probe sensor type W_1, The expected number of detections in area A is modelled as

$$N^{W_1} = N_{A,t+1}^{-}\varphi^{W_1} \quad (10)$$

Where φ^{W_1} is the penetration rate for W_1, which is the fraction of vehicles in the network that carry sensor type W_1. For some sensors, for example mobile phones, φ^{W_1} could be greater than 1.

If the wireless probe sensor W_1 can report vehicle speed then the mean speed averaged across all W_1 sensors detected in area A is modelled as

$$\bar{V}^{W_1} = \bar{V}_{A,t+1}^{-} \quad (11)$$

The same approach in (11) is used for census detectors that measure speed, for example inductive loop pairs..

Signal Control: Benchmark Tests

The type of discretized network state described in the previous section can be used as an input to machine learning junction control algorithms of the type described in [9,10]. Under this approach each junction has a corresponding set of areas which are deemed important to its signal control decision making. The metrics attached to the areas form the input nodes to a neural network. The output of the neural network is a decision as to which stage of the junction gets the green light at time t+1.

The neural network function can be trained in a number of ways including by a human expert using a computer game interface [9] and through trial and error, with feedback (reinforcement learning)[10]. The latter technique allows junctions to learn improvements in strategy while in operation.

In order to provide performance benchmarks for the evaluation of the methodology described in this paper micro-simulation tests were carried out on the three junction network shown in Figure 1 using S-Paramics micro-simulation software.

The lower benchmark test was a four (simulated) hours run, where the junctions were controlled by the SCOOT algorithm. The SCOOT API for S-Paramics was configured by a qualified SCOOT engineer from Siemens Traffic Solutions, UK.

The upper benchmark test was an otherwise identical four (simulated) hours run, where the junctions were controlled by the machine learning control system described in [9]. In this case *perfect* information was assumed in each of the discretized network areas.

Figure 4. Shows the transient journey times averaged across all vehicles leaving the simulation area in a 5 minute period. These values are plotted across the four hour test time for both SCOOT control and machine learning control.

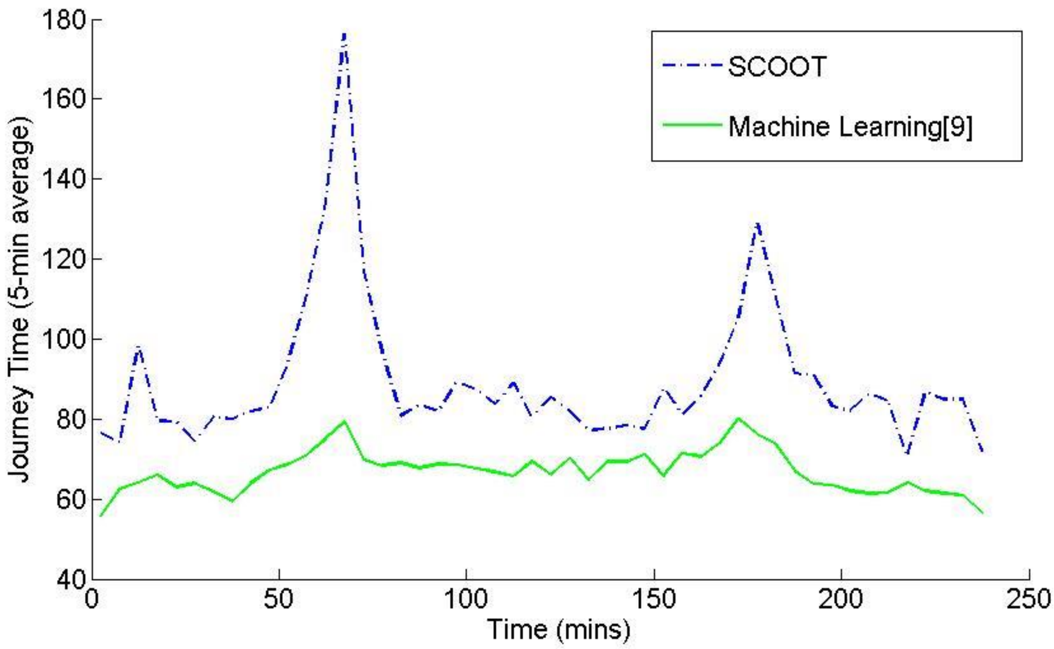

Figure 4 – Performance of upper and lower benchmark tests on the three junction network in Figure 1.

The evidence in Figure 4 shows that there is a significant performance differential between the upper and a lower benchmarks indicating that there is value in pursuing the gathering of wireless data for urban traffic control. Because perfect information is assumed in the upper benchmark test it does *not* represent a validation of the proposed EKF approach or the state-evolution model.

Conclusions

This paper has presented a methodology for estimating the state of the road network for UTC applications. The methodology can employ existing UTC sensors, for example inductive loops, microwave sensors and cameras. However it can also employ multiple types of wireless device sensors. By design the Extended Kalman Filter approach proposed is flexible to varying rates of penetration and latency in these sensors.

Results from simulation experiments have demonstrated a framework for the evaluation of the proposed methodology. Upper and lower benchmark tests of, respectively, a machine learning controller with perfect information and the SCOOT junction control system. The results of these tests in Figure 4 indicate that there is significant domain in which improvements over current systems are possible through the employment of wireless device data.

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