Efficient Tracking of Public Transport in Urban Environment

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Good public transport is an important requirement for smooth working of an economy. It not only reduces the traffic on the road leading to free flow of goods and services, it also reduces the oil dependence of the country and improves the environment conditions. The government of various countries is encouraging people to use public transport by infusing more capital for its development and making it more user friendly. Advanced traveler information systems (ATIS) is one such effort wherein a rider is provided with accurate real-time information which reduces their wait times [1], [2].

In this PhD we aim to abstract the transportation problem with new models and develop a framework for reducing communication cost. Reducing cost is really important for implementation of ATIS in case of countries (especially developing economies like India where there is major rise in the middle-class population and is adding a lot of cars on road every day) which have a business model that is different from the one used in US and the user (transit authority) is charged every time it tries to connect to the server.

ATIS provide real-time transit information concerning location of vehicles and estimated arrival times (ETA) [3]. Such information is based on the state estimate of the vehicles from on-board sensors, and models of vehicle motion through traffic. In the first part of this PhD, we propose new models and algorithms to track public transit in urban environment. The new models incorporate side information such as average speed on a segment of road, quality of GPS estimation, desired path and road inter-connectivity. This side information is either known apriori or can be learned in real time through communication among vehicles. We develop a model of interconnected road segments, each of which has a different dynamical model for the possible motion. We assume that the route is divided into links \( m = 1, \ldots, M \), and that for each link, there is a different dynamic model that governs the evolution of the continuous state. Specifically, the model at time \( k \) on link \( m(k) \) is described in state space form as:

\[
\begin{align*}
x(k+1) & = f_m(k)(x(k)) + w_m(k)(k) \\
y(k) & = h_m(k)(x(k)) + v_m(k)(k) \\
m(k) & = g(x(k))
\end{align*}
\]

where suffix \( m(k) \in M \) indicates the currently active link, \( f_m(k) \) is a process function, \( h_m(k) \) is a nonlinear measurement function, and \( g \) is an integer valued map that identifies the current link at time \( k \). The noise processes \( w_m(k)(k) \) and \( v_m(k)(k) \) are link dependent white Gaussian noise with zero mean and variance \( Q_m(k)(k) \) and \( R_m(k)(k) \), respectively.

This type of problem falls under the umbrella of stochastic hybrid systems. However, there is one notable difference between the models we consider in this work and the conventional stochastic hybrid system models: the dynamical systems we consider do not switch randomly between different dynamical models. Instead, transitions from one model to another are caused by the spatial motion of the vehicles of interest, and thus the transitions between discrete models depend on the continuous states. A consequence of the model we propose is that the discrete part of the system (namely, the link that identifies the dynamical model) is a deterministic function of the continuous part of the system, and does not have an independent evolution. This unique feature of the system in which the exact switching time is unknown requires new estimation algorithms. We develop new estimation algorithms of varying complexity (extended Kalman filter, unscented Kalman filter and particle filter) that incorporate the state-dependent switching among models by using adaptive predictors to estimate switching times. We show through simulation the relative advantages of the different estimation approaches. This work has been published in ACC and interested readers are referred to [4].

In the next part of the PhD we present a new architecture for ATIS and then develop transmission policies to reduce the communication cost. Fig.1(a) shows the block diagram of an existing ATIS [5]. In the existing system, the bus collects the GPS information and transmits it to the base station. The base station then uses the received observation along with some filtering algorithm like Kalman filter to estimate the current location of the bus. This location information is then used by the ETA algorithms to predict the time of arrivals for rest of the stops on the itinerary. Existing methods employ protocols of transmissions that are fixed apriori. Most of the existing system transmits the location information either every \( k^{th} \) time instant or after every \( m \)

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![Fig. 1](image-url)
The problem with these protocols is that they do not account for the traffic condition and the time of journey. For example if the bus is running early morning or late night or in middle of the day when there is less traffic on the road, the number of communications to the base station can be reduced drastically. This frequent communication is one of the main hurdles for implementation of such systems, especially in developing countries. One should note that the communication cost is not just one-time cost but a recursive one. The proposal to use wire line communication has been dismissed by most in literature because the system in that case is not only hard wired and there is no flexibility to change routes or change bus stops but it also causes problems in maintenance.

In this work, we present a new architecture for the ATIS. We propose to add computational capability at the bus itself. In particular, we move the filter (which consists of a predictor and update) from the base station to the bus while retaining a copy of the predictor at the base station as shown in Fig.1(b). Consequently, estimation is performed at the bus itself and the base station is updated with the most recent update either based on a pull from base station or a push from bus. Currently we have analyzed the push protocols and the work for pull protocol is in process. The goal of this part of the PhD is to develop communication policies so as to minimize the difference between the information available at the bus and at the base station subject to communication constraints.

Let \( P_C^0(k) = p(x(k) | Y^{0,m}) \) and \( P_L^0(k) = p(x(k) | Y^{0,k}) \) be the conditional distribution of the \( l^{th} \) available at the base station and bus, respectively, at time \( k \) given the measurements from time 0 to \( m \) (\( m \leq k \)). Let \( u(k) \in \{0,1\} \) be the time-varying control signal. \( u(k) = 1 \) indicates transmission and the information at base station \( P_C^0(k) \) is updated with \( P_L^0(k) \), i.e., \( P_C^0(k) = P_L^0(k) \) while \( u(k) = 0 \) indicates no transmission. We shall use the Kullback-Leibler divergence distance to measure the difference. Therefore, mathematically the problem can be formulated as follows:

\[
\text{minimize}_{\epsilon} \quad E_{\gamma} \left\{ \sum_{k=1}^{T} D_{KL}(P_C^0(k) || P_L^0(k)) \right\} \\
\text{subject to:} \quad E_{\gamma} \left\{ \sum_{k=1}^{T} c_1 u(k) \right\} \leq M;
\]

such that \( M \) are the total available resources and \( c_1 \) is the cost of communications. \( P_C^0(k) \) and \( P_L^0(k) \) are propagated using the system equations and Certainty Equivalence Principle (CEP).

The first transmission policy is parametric approach wherein the transmission decision is taken based on a threshold. This parametric strategy compares the current information available at the bus with the knowledge of base station. If the difference in the information is more than some threshold then transmission takes place and the base station is updated with current location information. The threshold for this parametric policy is decided based on the communication constraints and is optimized offline. This technique generates a myopic policy for communication.

In the second part rather than having a threshold trying to decide the communication policy, we try to solve the problem in the optimization framework. The size of the problem huge if we try to solve the problem for \( T \) time steps (complete time of the trip). Instead, we divide the total number of allowed number of communications in windows of size \( p \) each such that only one transmission is permitted per window. This is a fixed horizon optimization. Note that optimization decision is taken at the start of the window and this approach does not account for the new information. This assumption will be relaxed in the third problem set up known as receding horizon optimization. The threshold for the parametric approach is optimized off line and it is fixed for the itinerary while the non-myopic approaches are more real-time and they adapt according to received observations.

Fig. 2 shows the simulation results for push protocol.

Impact: The research work done from has multiple implications. Some are listed few:

1) This work lays down foundation for implementing ATIS in communication constrained environment.
2) We proposed new models and estimation algorithm to model traffic and track the public transit. The non-linear estimation algorithms opens door for development of more advanced and sophisticated models.
3) This work indicates same accuracy may be achieved in a probabilistic communication environment like vehicle to vehicle (V2V) communication or vehicle to infrastructure (V2I) communication which has received much attention recently.
4) ATIS may also be implemented in the cognitive communication environment as a secondary user. Therefore it facilitates the efficient usage of the spectrum.

REFERENCES