Utilising Traffic Prediction Models (Kalman Filter and Particle Filter) in Public Transportation

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Abstract: Bus arrival time is a key service for improving public transport attractiveness by providing users with an accurate arrival time, which can help them to arrange their travel schedule intelligently. In this research, a model of bus arrival time prediction, which could improve arrival time accuracy is proposed. The bus arrival time will be predicted using a Kalman Filter (KF) model and Particle Filter (PF) model, by adding additional information from social network communication. The KF Models and PF model predicts the arrival time by filtering the noise or disturbance during the journey. Theoretically, social networks feed road traffic information into the model, based on information provided by people who have experience on the scene. This paper is an extended version from “Towards Improved Vehicle Arrival Time Prediction in Public Transportation: Integrating SUMO and Kalman Filter Models [1]. This research compares different prediction models which are KF models and PF model. In addition, this work identifies the best models to use for traffic prediction. It is believed the information from social network communication can improve the accuracy of traffic prediction.

Key words: Kalman Filters (KF) · Particle Filter (PF) · Social Network Communication

INTRODUCTION

Traffic flow in major urban roads is affected by several factors. It is often interrupted by a few conditions, such as traffic lights, road conditions, number of vehicles on the road, time of travel, weather conditions and driving style of vehicles. The provision of timely and accurate travel time information of transit vehicles is valuable for both operators and passengers, especially when dispatching is based on estimation of potential passengers waiting along the route rather than the predefined time schedule. Operators manage their dispatches in real time and passengers can form travel preferences dynamically. Arrival time estimation for time scheduled public transport busses have been studied by many researchers using various paradigms. However, dynamic prediction on some type of transit vehicles, which do not follow any time schedule, or stop station constrains introduces extra complexities.

Currently, the monitoring of traffic flows in urban areas is improved through the use of recording cars with cameras that recognize number plates. With the available real-time travel time measurements, a dynamic calibration of travel time models is able to improve the performance of prediction. The dynamic of KF models have been demonstrated to successfully not only be able to estimate traffic states on freeways, but also improve the accuracy of urban travel time prediction models due to their significant property of updating the state variable continuously to create new observations.

There are many algorithms based on mathematical theory and/or statistical models that have been proposed for bus travel time prediction. However, there is a gap amongst those algorithms. One particular issue is the question of how the algorithm will receive and incorporate live real-time traffic event information. Without receiving such information, those algorithms could not produce an accurate result. If there is an accident and it is known that it takes 30 minutes to clear, how can this information be passed into the filter and be made available so that KF approaches can make use of it? This paper proposes that social network communication can be used for this purpose, by making necessary information available to arrival time prediction algorithms [2]. Social network communication is a novel way to collect and include current road condition information, rather than using GPS or other (road) sensors to detect the numbers of cars on the road and speed of travel. In addition, this approach allows for the identification of unexpected traffic events and the subsequent inclusion of this new, real-time
information, as part of potential route calculations and updates [1]. This provides updated information during journeys that may not have been available when travel was initially planned or started. In this situation, social networks can play a pivotal role as an input to a scheduling model [3].

**Related Works:** Most of arrival time prediction models are based on historical models, time series analysis, artificial neural networks and regression models. Historical prediction model gives the current and future bus travel time from the historical travel time of previous journeys on the same time period. The current traffic condition is assumed to remain stationary. Williams and Hoel pointed out that the phenomenon that traffic conditions follow nominally consistent daily and weekly patterns leads to an expectation that historical averages of the conditions at a particular time and day of the week will provide a reasonable forecast of future conditions at the same time of day and day of the week [4]. Therefore, these models are reliable only when the traffic pattern in the area of interest is relatively stable, e.g. rural areas. Historical data based models are usually used in combination with the most recently observed traffic data to provide real-time travel information. Though a variety version of historical data based models have been developed for prediction of travel time, for the sake of simplicity, they are classified here broadly as models that use average travel time and models that use average speed in order to give the estimated value of travel times.

These models assume that the exogenous factors acting upon the dynamical system either remain constant, or can be measured and accounted for in the model, if they vary in time. In terms of traffic, they assume that the historical traffic patterns will remain the same in the future. As has been indicated on [5], the accuracy of time series models is a function of the similarity between the real-time and historical traffic patterns. Variation in historical travel time data or changes in the relationship between historical and real-time travel time data could significantly cause inaccuracy in the prediction results. To the author’s knowledge, these models have not been used for prediction of bus travel time so far. However, they have been used and indicated to be effective for link travel time and traffic volume predictions either alone or in combination with other models, e.g. Kalman filtering.

Artificial Neural Networks (ANNs) have been recently gaining popularity in predicting bus arrival time because of their ability to solve complex non-linear relationships [6]. ANNs, motivated by emulating the intelligent data processing ability of human brains, are constructed with multiple layers of processing units, named artificial neurons. The neurons contain activation functions (linear or nonlinear) and are highly interconnected with one another by synaptic weights. Information can be processed in a forward or feedback direction through fully or partially connected topologies. In general, ANN models have the ability to capture the complex non-linear relationship between travel time and the independent variables. These models have been proved to be effective for the provision of satisfactory bus arrival time information. They could be very useful in prediction when it is difficult or even impossible to mathematically formulate the relationship between the input and output.

ANNs models predict and explain a dependent variable with a mathematical function formed by a set of independent variables [7]. Unlike historical data based prediction models, these are able to work satisfactorily under unstable traffic condition. Regression models usually measure the simultaneous effects of various factors, which are independent between one and another, affecting the dependent variable. In general, the applicability of the regression models is limited because variables in transportation systems are highly inter-correlated.

Kalman filtering models have elegant mathematical representations (e.g. linear state-space equation) and the potential to adequately accommodate traffic fluctuations with their time-dependent parameter. It has been used extensively for predicting bus arrival time [2][3][8]. Its basic function is to provide estimates of the current state of the system. However it also serves as the basis for predicting future values or for improving estimates of variables at earlier times, i.e., it has the capacity to filter noise [9]. Kalman Filters are really a dynamic model as it is design to consider of any information that related. Kalman can pickup any dynamic information to be processed to produce the result. Kalman filter models can be applied on-line. So, it still can be processed while vehicle trip is in progress due to its simplicity in calculation. KFs are a very powerful tool when it comes to controlling noisy systems [10]. The basic ideas of KFs are that they process or filter all incoming noisy data and produce an improved quality of output data.

**MATERIALS AND METHODS**

**KF is Suitable Model for Prediction:** KF is a fancy statistical way of using past and present data (observations) and a dynamical model, in order to estimate how the 'state' evolves over time and to make future
KF combines the observations and model to produce the result. For example, a state estimate is formed from two components which are data (observations) and model. So to determine the present 'state' of your car, you would take any available data for the position and speed (e.g. from GPS) but recognize none of these observations are perfect. Every measurement has uncertainty, be it due to measurement inaccuracies or sampling issues. Those observations would be combined with a 'model' of the travelling behavior such as if the car stop at the traffic light, how long does it take?; if the car slow down at the school area, how slow it is? The key point is the model like the observations, is not perfect. Sometimes the real-world travelling behavior will not correspond exactly to the model. The model for the travelling must include dynamic parameters like traffic congestion, weather, road closure, road works and so forth. The KF model is a way of forming a 'state estimate' (car's arrival prediction) by incorporating the prediction of the model with real-time information which is available in social networks. With all of these available information (model and measurements/observations), KF is a method to integrate them to arrive at a successful state estimate. It uses the state estimate from the previous time step and the system model to arrive at a prediction and then corrects this prediction by integrating the measurements.

**Linear Kalman Filter and Non-Linear Models:**
KF models are commonly used to estimate the states of a dynamic system. Linear and Non-Linear KF models each have their own advantages. No general statement can be made as to which is best, because it depends on the particular situation at hand. Choosing the most suitable model is vital in order to produce the most accurate arrival time. Comparison of different types of KF models, including conventional linear and various types of non-linear KFs (which are essentially variants of extended KFs linearizing nonlinear assumptions), is vital to identify the optimal model for arrival time estimation.

**Linear Kalman Filter:** The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback—i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems.

If we want to use a standard Kalman filter to estimate a signal, the process that we’re measuring has to be able to be described by linear system equations. A linear system is a process that can be described by the following two equations [1][2][3]:

**State equation:**

\[
x_{k+1} = \alpha x_k + \beta u_k + w_k
\]

**Output equation:**

\[
y_k = \mu x_k + z_k
\]

These equations define a linear system because there are not any exponential functions, trigonometric functions, or any other functions that wouldn’t be a straight line when plotted on a graph. The above equations have several variables:

- \( \alpha, \beta \) and \( \mu \) are matrices  
- \( k \) is the time  
- \( x \) is known the state of the system  
- \( u \) is a known input to the system  
- \( y \) is known the measured output  
- \( w \) and \( z \) are the noise - \( w \) is called the process noise and \( z \) is called the measurement noise.

Each of these variables are (in general) vectors and therefore contain more than one element.

**Extended Kalman Filter:** The extended Kalman filter (EKF) is an extension that can be applied to nonlinear systems. The requirement of linear equations for the measurement and state-transition models is relaxed; instead, the models can be nonlinear and need only be differentiable. The EKF works by transforming the nonlinear models at each time step into linearized systems of equations. In a single-variable model, you would do this using the current model value and its derivative; the generalization for multiple variables and equations is the Jacobian matrix. The linearized equations are then used in a similar manner to the standard Kalman filter.
As in many cases where you approximate a nonlinear system with a linear model, there are cases where the EKF will not perform well. If you have a bad initial guess of the underlying system’s state, then you could get garbage out. In contrast to the standard Kalman filter for linear systems, the EKF is not proven to be optimal in any sense; it’s merely an extension of the linear-system technique to a wider class of problems.

If we want to use an Extended Kalman filter to estimate a signal, the process that we’re measuring has to be able to be described as below\[1\][2][3]:

State equation: $x_{k+1} = f(x_k, u_k) + w_k$  \hspace{1cm} (3)

Output equation: $y_k = h(x_k) + z_k$  \hspace{1cm} (4)

The state equation $f(x, u)$ and the measurement equation $h(x)$ are nonlinear functions.

**Particle Filters:** Particle filters is a non-linear model to track the state of a dynamic system like Linear and Extended Kalman Filter. Suppose you have a model of how the system changes in time, possibly in response to inputs and a model of what observations you should see in particular states, you can use particle filters to track your estimation state. The main reason to use the Particle Filters is to solve a lot of uncertainty and dimensional problems. Moreover, particle filters are tractable whereas Linear and Extended Kalman filters are not. The key idea to use Particle Filters is to find an approximate solution using a complex model rather than an exact solution using a simplified model. Sometimes a simplified model just isn’t good enough due to numerous uncertainties of system.

**Work Proposed:** The addition of state constraints to a KF can significantly improve the estimation accuracy of the filter. In this sense, the addition of linear information may be useful to tackle this problem. KF models (linear and non-linear) theoretically deliver the best and most up to date results when they have continuous access to dynamic information. Many existing models therefore make use of dynamic information. However, the performance of these models can often suffer due to issues with taking account of scenarios that utilise rapidly updating real world information. The constraints may be time-varying or non-linear. Many road users utilise navigation system to navigate and estimate the duration of their journeys. However, it is not always possible to handle some events solely by navigation system information. For instance, if there is an accident and we know it will take 30 minutes or more to clear; navigation system cannot pick up this information because it provides and predicts arrival time based on GPS satellites. It works by calculating the GPS receiver position, which is done by precisely timing the signals sent by GPS satellites. Social networks have the capability to provide plausible real time information regarding road traffic, which could potentially improve the accuracy of arrival time prediction.

Intelligently/automatically selecting the best source of external traffic condition information from social networks for input into the KF model can produce the best traffic prediction results by comparing between conventional GPS based Traffic Management Systems (TMS) and new social media information sources. As this paper discussed previously, the external/delay information could initially be 'linearly' added to determine total KF based arrival estimation times. For instance, if we suppose a KF model estimated arrival time without external delay information is 80 seconds and if the external GPS/TMS based delay info is 30 seconds, then the updated/total arrival time = 80 seconds + 30 seconds = 110 seconds. On the other hand, if the social media delay information of 20 seconds is determined to be more timely and accurate/reliable then the updated/total KF model estimated arrival time will be= 80 seconds + 20 seconds = 100 seconds [1][2][3].

In this paragraph briefly describes how the ‘linear’ information can be added into KF model:

In order to use a KF to remove noise or disturbance during a travel time, the process that we are measuring must be able to be described by a linear system. A linear system is a process that can be described by the following two equations:

**State Equation:**

$x_{k+1} = a x_k + \beta u_k + w_k$  \hspace{1cm} (1)

**Output Equation:**

$y_k = \mu x_k + z_k$  \hspace{1cm} (2)

In the above equations variables $a$, $\beta$ and $\mu$ are matrices; $k$ is the duration of the simulation; variables $x$ known as the state of the system; variables $u$ is an input to the system; variables $y$ function to measure output; and variables $w$ and $z$ are the noise. The variable $w$ is known as process noise and variable $z$ is known as measurement noise. Every variable are vectors and has
more than one element. The variable $x$ is a vector and has the information about the present state of the system; however variable $x$ cannot be measured directly due to corrupt by the noise of variable $z$. In this condition, variable $y$ can be used to acquire an estimate of variable $x$. However, information from $y$ cannot be taken at nominal value as variable $y$ is corrupted by the noise. From that explanations, ‘linear’ information will be added in variables $u, w$ and $z$. In the real world, variable $u$ represents the car acceleration, variables $w$ and $z$ represent process noise and measurement noise which are estimation of disturbance during the travel time and information from social networks regarding on the noise during the journey.

**Kfs Theory Determine the Best Estimation/Prediction of Certain State:** Suppose a linear system model as described in previous paragraph taken as example. The measurement of variable $y$ been used to estimate the state of variable $x$. Suppose we get all the information about the behavior of the system, how the system working based on the state equation and we know the position measurements. How can we determine the best estimate of the state $x$? How estimator can gives an accurate estimation of the true state considering of it cannot directly be measured. What sort of metric should an estimator fulfill? To answer those questions, first and foremost it is a must the average value of the state estimate be equal to the average value of the true state.

![Fig. 1: Car position estimation using Linear Kalman Filter](image1.png)

![Fig. 2: Particle Filter predicts the car position](image2.png)
In term of mathematical theory, expected of the estimate value should be equal to the state value. The state estimate should be closely different from the true state. The average of the state estimate should be equal to the true estimate and the error variance of estimator should as small as possible. However, the solution of KF model cannot be utilized unless it can meet certain assumptions about the noise that affecting the system. These kinds of process make the KF most suitable model for prediction.

**Experimentation:** In earlier paragraph mentioned about to use Linear Kalman Filter Model or Non Linear Models depend on situation at hand. This situation relies on how difficult to translate the event into the model. To show how truth this statement, the experimentation have been conducted between Linear Kalman Model and Non-Linear Model which is Particle Filter Model. Situation below try to simplify the position of the car during the journey:

A car moves linearly from point A to B. The journey takes around 50 seconds. An acceleration of the car is 1.5 seconds. Process noise during the journey is 0.05 seconds and measurement noise is 0.1 seconds. The number of continuous update the data is 5 times.

According to figure 1, Linear Kalman Filter can predict the position of the car quite well. The true position is 0.04 feet meanwhile Kalman Predict at 0.08 feet. However, the Linear Kalman didn’t predict well all the time step. It only can perform well at the end of the simulation. This happen because Linear Kalman is statistical model that estimate based on prior and current observations. If we refer to figure 2, the particle filter predict almost similar to the true position of the car all the time of the simulation. Only at time step 30 seconds, the particle didn’t predict well. Particle predict quite accurate due to its nature without requires any assumptions about the state model.

**CONCLUSION**

KF models and PF model are well established models to predict public transportation, especially bus arrival time. The strength of KFs and PF is their ability to predict or estimate the state of a dynamic system from a series of noisy measurements. Based on this strength, additional credible and trusted information from social networks can be leveraged to feed into KF models. The nature of social networks, especially Twitter, which provides the real time information, is vital to get up-to-date news relating to road traffic. It is expected that information from social networks information can be added into KF Models and PF model to improve the accuracy of bus arrival time predictions.

**REFERENCES**