The acquisition of accurate traffic states in real time is fundamental to building Urban Advanced Traveler Information Systems (UATIS). For this purpose, various sensors (e.g., loop detectors, probe vehicles, cameras, cell phones) are used to collect required traffic information. However, it is difficult to provide complete, accurate and reliable traffic information using only one type of sensor due to the various disadvantages particular to each type.

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In Shanghai, SCATS (Sydney Coordinated Adaptive Traffic System), a type of loop detector system, and GPS-equipped taxis are used to acquire real-time traffic data. The SCATS loop detectors are embedded at the entrance to every intersection within the downtown area. These detectors only provide traffic information about the ends of road sections, which might not be an accurate or sufficient reflection of the overall traffic state through a road section. On the other hand, there are more than 14,000 GPS-equipped taxis active on the Shanghai road network, which can perform real-time measurements of the road network. However, the sample number obtained is still a bottleneck representation when compared against an accurate estimation of the traffic state for each link of the urban road network. Therefore, a fusion estimation may provide a more effective approach towards traffic state estimation, allowing for a more cooperative effort between the two types of traffic detectors.

To address this problem, many researchers have attempted to develop more efficient fusion models in order to integrate the two sources of traffic information and obtain better results. R.-L. Cheu et al. [1] made use of a neural network based fusion model, and validated its performance using simulations; K. Choi and Y. Chung [2] presented a fusion algorithm based on fuzzy regression, which embodied the positive effects of fusion in experiments using real-world data collected from several arterial links; H.-S. Zhang et al. [3] proposed a fusion-based architecture in order to manage, analyze and unify the traffic data; N.-E. El Faouzi not only discussed the best linear estimation and the weighted least squares methods [4], but he also put forth a classifiers fusion method based on the Evidence Theory [5]. However, all of the research thus far has focused on the theory development: few have applied their approaches in practical applications.

In this paper, we will introduce a fusion-based system composed of real-time traffic state surveillance. This system can realize the real-time traffic state estimation with over 10,000 bidirectional road sections, all the links of the Shanghai urban road network. The system consists of three modules: SCATS data processing (MS), GPS data processing (MG), and Fusion Module (FM). In MS, traffic information collected by SCATS is converted into a kind of link-based spatio-temporal mean-speeds. Similarly, the taxis’ information is also calculated for the spatio-temporal mean-speeds by means of a GIS-T map in MG. The spatio-temporal mean-speed here is defined by the mean-speed of all the vehicles running on a link during a period of time. Finally, the mean-speeds from these two sources are fused using an improved evidential fusion model. The structure of the whole system is shown in Figure 1.

Details of each module will be discussed in the following sections: First, the transferring algorithm used in MS will be introduced briefly in Section II. Then, the module for GPS data processing is described in Section III. In Section IV, the fusion model is presented. Experiments are performed in Section V to show the advantages of the system. Finally, we will conclude the paper in Section VI.

Module of SCATS Data Processing
As an efficient adaptive traffic control system, SCATS has been widely used in many major cities across the world. In downtown Shanghai, SCATS is a key traffic control system. To avoid any repeated investment, we extract traffic information from the data detected by SCATS loop detectors. However, differing from other loop detector...
systems like SCOOT, SCATS loop detectors are buried at
the end of road sections, instead of the middle, as shown
in Figure 2. This particular setup creates huge difficulties
for the traffic state estimation. As M. Papageorgiou and G.
Vigos [6, 7] noted, the time-occupancy measured by the loop
detectors at the middle of links can give a better estimation
to the space-occupancy than those measured at either side.
In this context, we must find a better way to deal with the
situation: thus we use a traffic wave theory based method
in order to estimate the mean-speed in MS [8]. From the
experiments, we found that the method is effective. Next,
we will give a brief introduction.

In our case, we obtain the following information from
SCATS data: detector ID, phase, cycle, flow, Saturation, and
time-occupancy. Based on the traffic wave theory [9], the
mean-speeds are computed using the following algorithm.

If we define \( u_i \) to be the mean-speed of the vehicles be-
fore they begin to queue, \( k_i \) the mean density of the vehicle
flow before queuing, and \( u_q \) the mean-speed of the vehicles
when they drive away from the queue, then the three inter-
medial variables can be calculated by

\[
\begin{align*}
  u_i &= u_f(1 - d_i) \\
  q &= u_f h_i (t_r + t_g) \\
  T_o &= T_p + (q - k_i u_f d_i (T_d + t_r) (l_r + l_g)) / u_2
\end{align*}
\]

with

\[
\begin{align*}
  T_p &= u_f d_i (T_d + t_r) / u_2 \\
  T_d &= t_r d_i (1 - d_i) \\
  d_i &= k_i / k_f
\end{align*}
\]

where \( u_f \) is the speed of free traffic flow; \( k_f \) is the vehicle
density during a traffic jam; \( q \) represents the vehicle flux
in a single cycle of red and green traffic lights; \( t_r \) and \( t_g \)
denotes the time length of the red light and the green light
respectively; \( T_o \) denotes the time during which the loop
detector is occupied in the cycle; \( T_p \) represents the time
during which all of the vehicles in the queue occupy the
loop detector when they leave the crossing; \( T_d \) denotes the
time during which the vehicles in queue dissolve com-
pletely; \( l_r \) and \( l_g \) is the mean length of a vehicle and a loop
detector, respectively; and \( d_i \) denotes the normalized den-
sity as defined in the traffic flow theory.

For vehicles in the queue, the travel time it takes for
every vehicle to pass the entire road section can be easily
obtained. Similarly, vehicles not in the queue can also be
computed.

Then, we use the length of a link and the time during
which every vehicle passes through the link to calculate
the mean-speed of the link during that traffic cycle.

**Module of GPS Data Processing**

Using GPS-equipped taxis as probe vehicles is a good way
to obtain real-time measurement of traffic states in a road
network, because a large number of taxis can provide rela-
tively sufficient samples over a road network in real time.

Data from the GPS probe vehicles contains the vehicle
ID, position coordinates, time, velocity, moving direction,
and vehicle status (passenger occupied or not). In order
to estimate traffic states using this data, three processing
steps are implemented: coordinates transformation, map
matching, and curve approximation.

To begin with, the coordinates from GPS systems
are recorded as WGS-84 coordinates, which are three
dimensional. However, the GIS-T map uses city coordinates,
a planar coordinate system. In addition, coordinate origins
and scales are also different between these two systems.
Therefore, we need to transform coordinates from the
WGS-84 to the GIS-T map before we begin any processing.
We used the affine transform algorithm to complete
this transformation.

Next, map matching – the most important step in the
process – is carried out. The accuracy of map matching
affects the result of estimation directly. In our case, we
combined the nearest neighbor method and the vehicle
tracking method in order to implement map matching. The
former is the principal part of the proposed method, while
the latter is used to process any uncertain points surround-
ning road intersections. The experiment illuminates that
the method bears a good tradeoff between accuracy and
operation speed. A result of map matching is shown
in Figure 5. In the figure, points located outside of
roads (the red points) mark the original positions of
the probe taxis, and the points dragged onto roads (the
green points) are their corresponding positions after
map matching.

The final step in this module is curve approximation.
We use curve fitting to approximate sample data sets and
estimate the mean-speed. In this work, the least-square
method is used to fit the data. A computation result is shown
Fusion of SCATS data and GPS probe vehicle data yields comprehensive and accurate estimates of urban road traffic states.

in Figure 4 [10], which visualizes the spatio-temporal speed distribution along the Huai-Hai-Zhong road of Shanghai (from east to west) over a period of 24 hours. With this method, we can attain the mean-speed of travel through each road section in that road network.

Fusion Module
Due to a high failure ratio for loop detectors and a low sampling ratio of probe vehicles during some of the time periods, any state estimation based on such information is often inaccurate and considered deficient. Therefore, we built a fusion-based estimation model [11]; it integrates the two types of detector data, and is expected to use the resultant rich information set to improve results. In this section, we will describe the fusion model briefly, which combines the Federated Kalman Filter [12] and the D-S Evidence Theory [13]. Some general terms and symbols in the two theories have been used without explanations beforehand.

The calculating process of the Federated Evidence Fusion Model includes four stages: evidence reliability estimation, data smoothing and variances evaluation, creation of masses, and data fusion and decision-making.

Evidence Reliability Estimation
The detector data collected in fields is considered unreliable due to loud noises; therefore, we must first estimate their reliability in order to improve the accuracy of our estimation. In [14], reliability was discussed as both static reliability and dynamic reliability. The former is the inherent reliability of sensors and can be obtained before subsequent applications; the latter denotes the reliability that changes with the varying environment such as unexpected disturbances, environmental noises, and meteorological conditions. In our case, the static reliability is ascertained from the training set beforehand; whereas the dynamic one is evaluated by a group of Kalman Filters, which is synchronously implemented with data smoothing.

Data Smoothing and Variances Evaluation
Before extracting mass features, a set of Kalman Filters are built in order to get rid of unexpected noises from the detector data. At the same time, it can also estimate the variances in a system, which are then employed during the calculation of the dynamic reliability by (2)

\[
\begin{align*}
    w^d_{i}(t) &= \exp(-\phi_i p_{i,t}) \\
    \rho_{i,t} &= P_i(t) / \sum_{i=1}^{M} P_i(t)
\end{align*}
\]

in which \( w^d_{i}(t) \) represents the dynamic reliability weight of the evidence; \( \phi_i \) and \( \mu \) are two parameters, which can be decided based on real data; \( P_i(t) \) denotes the estimated variance of the detector \( i \) at time \( t \), which is provided by the set of Kalman Filters; \( M \) is the amount of detector sorts.

After the above processing, the smoothed result of traffic state \( x_i(t) \) will be transformed into a set of Basic Probability Assignment (BPA), and the \( w^d_{i}(t) \) will be sent to the fusion step to participate in the fusion operation.
Creation of Masses
In this step, we use the negative exponential proposed by Denoeux [15] to create masses.

\[ m_i(\omega_i) = \exp(-\gamma d_i^2), \]  
\[ (5) \]

where \( d_i \) is a type of distance between data detected by the \( i \)th type of detectors and the prototype from each class. The prototype can either be designated artificially or be derived from clustering historical data. The parameters \( \beta \) and \( \gamma \) are determined according to practical data from the training set.

In addition, the masses still need to be normalized before attending to fusion computation.

Data Fusion and Decision Making
In the fusion step, we employ the following algorithm to obtain the state result:

First, let \( m_i(A_{i,t}) \) (\( i = 1, 2, \ldots, M \)) represent the BPA extracted from the data of detector \( i \) at time \( t \), the BPA combined with the dynamic reliability \( m_i'(A_{i,t}) \) (\( i = 1, 2, \ldots, M \)) can be computed as the following:

\[
\begin{align*}
  m_i'(A_{i,t}) &= w^d_i \cdot m_i(A_{i,t}), \\
  m_i'(\Omega) &= 1 - \sum_{A_{i,t} \subset \Omega} w^d_i \cdot m_i(A_{i,t}). \\
\end{align*}
\]

After that, all of the BPAs from different detectors are fused together in accordance to the following rules, which are based on the combining rule of D-S Evidence Theory.

\[
m_i'(B_{i,t}) = m_i'(C_{i,t-1}) \oplus m_i'(A_{i,t}) = \frac{\sum C_{c_{i,t-1} = c_{i,t}} g[m(C_{i,t-1}) \times m_i'(A_{i,t})]}{1 - \sum C_{c_{i,t-1} = c_{i,t}} g[m(C_{i,t-1}) \times m_i'(A_{i,t})]},
\]

\[ (6) \]

where \( m_i'(B_{i,t}) \) (\( i = 1, 2, \ldots, M \)) denotes the respective fusion results of detector \( i \) at time \( t \), and \( m_i'(C_{i,t-1}) \) represents the last fusion result of the fusion system at time \( t-1 \). They are both in the form of BPA. The parameter \( \lambda (0 \leq \lambda \leq 1) \) represents the degree to which \( m_i'(C_{i,t-1}) \) is weakened. The value of this parameter can be derived from supervised learning using the real data in a training set. Thus, we can weaken the feedback to avoid dominating the fusion during the next time period.

<table>
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<tr>
<th>Table 1. The MSDE of the system.</th>
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<tr>
<td>Arteries</td>
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<td>Branches</td>
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Finally, we can obtain the conclusion of state estimation at that time using the maximum belief rule.

Experiments
In the experiments, the operation speed and veracity of the system are evaluated. The former can be easily evaluated; however, the latter is hard to measure because it is impossible to get the real spatio-temporal mean-speed on a road section. In this case, we use a Mean State Decision Error (MSDE) to evaluate the veracity of the system. The MSDE is defined as the percent of the number of erroneous system decisions over the real traffic states. The real traffic states were artificially judged from the traffic surveillance videos.

Data Preparation
The experiment data consist of three parts, of which the SCATS data and the video data were both provided by traffic police headquarters. On the other hand, the GPS data came from the two largest taxi service corporations, which include approximately a total of 10,000 GPS-equipped taxis active in the urban area every day. We selected the dates September 25, 26, and 27, 2007 for the experiments, and applied the SCATS and GPS data obtained from these three days in our system. Meanwhile, video footage of eight arteries and ten branches were chosen from the entire road network to validate the accuracy of our experiments.

Results
The system was operated on a personal computer with an Intel Core2 Duo 2.66G processor and 4GB RAM. The GIS-based urban network of Shanghai constituted of approximately 10,000 links connected with more than 7,000 crossroads. Data from SCATS and GPS were collected and processed every five-minute period. Under these conditions, all of the calculations in one period require 17.6 seconds. Thus, our system performance and speed would be adequate for a real-time operation.

Table 1 shows an experimental evaluation of the accuracy of the system by MSDE. In arteries, the accuracy can reach...
97.5% by means of fusing the two types of data. For branches, the accuracy drops to 95.3% due to a lack of necessary loop detectors and probe taxis. An artery is defined as a road link having more than three lanes in one direction; while branches are roads with three or less lanes in one direction. We also found that the estimation accuracy using SCATS data is higher than that when using GPS data for both types of road links. This is because the process of map matching and the deficiency of GPS sample create more error. However, it should be noted that the spatial coverage of GPS probe taxis extends way beyond that of loop detectors. This advantage is able to counterbalance the GPS probe taxis’ shortcomings to a certain degree.

The estimation results are illustrated on the displaying platform as shown in Figure 5 and Figure 6. In these figures, the colors of road sections, red, orange, yellow, green, or dark green, represents corresponding traffic states ‘very congested’, ‘congested’, ‘medium’, ‘smooth’, or ‘very smooth’, respectively.

Conclusion

This paper proposed a fusion-based system for real-time traffic state estimation in urban road networks. In this system, both SCATS data and GPS probe vehicle data are integrated by a model of federated evidence fusion. By this means, we are then able to form a more comprehensive and accurate estimation of urban road traffic states. When deployed in combination with the structure of a Federated Kalman Filter, the fusion model can overcome difficulties arising from the D-S Evidence Theory in the case of huge conflicts. Therefore, it is able to realize a real-time fusion of heterogeneous detector data at the feature level. From the experimental results, we found that the operation speed and the veracity of the built system are able to satisfy the requirements of practical applications in an urban city, such as Shanghai.

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References