MULTI-SENSOR FUSION BASED ON THE DATA FROM BUS GPS, MOBILE PHONE AND LOOP DETECTORS IN TRAVEL TIME ESTIMATION

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ABSTRACT

Travel time estimation is the basis for many Intelligent Transport Systems (ITS) applications and traffic management functions. There have been numerous studies that show that fusing data from different sources such as GPS, Bluetooth, mobile phone network, and Inductive Loop Detector can result in more accurate travel time estimation. However, to date there has been little research investigating the contribution of individual sources to the quality of the final estimate or how this varies according to source-specific data quality. In this paper, three different data sources, namely bus-based GPS data, inductive loop detector data and mobile phone data, of varying quality are combined using three different data fusion techniques of varying complexity. In order to quantify the accuracy of travel time estimation, Automatic Number Plate Recognition data are used as ‘ground truth’. The final results indicate that fusing multiple data together does not necessarily enhance the performance of travel time estimation and in particular, that attention must be paid to the correlation structure amongst different sources. The results also show that even in dense urban areas, bus-based GPS, when combined with inductive loop detector data can provide reasonable estimates of general traffic stream travel time.

Keywords: Multi-Sensor Data Fusion, Travel Time Estimation, Multiple Data Sources
INTRODUCTION

Travel time estimation is the basis for many Intelligent Transport Systems (ITS) applications and traffic management functions (1). Therefore the accurate and reliable estimation of travel time is an area of active research (2, 3, 4, 5). In recent years, the availability of a range of new data sources has led to the application of sensor fusion techniques which aim to improve the quality of travel time estimates by combining data from multiple sensor sources. However, to date there has been little research investigating the contribution of individual sources to the quality of the final estimate or how this varies according to characteristics and quality of the specific sensor sources.

The aim of this research is to explore the effect on the quality of final travel time estimates of combining data sources with different characteristics and quality using a range of different sensor fusion approaches, of varying complexity. Understanding the trade-offs that exist between sources-specific data characteristics and fusion complexity is of considerable practical importance, especially as such sources proliferate and practitioners must make difficult decisions regarding how to spend limited budgets on procuring and analyzing data. The focus of the work is on urban road networks, using data from London as a case study.

The rest of this paper is organised as follows. After a background section where existing data sources and data fusion techniques for travel time estimation on urban roads are reviewed, three data fusion methods are introduced. In the third section, Artificial Neural Networks (ANNs) and Weighted Mean Approach (WMA), selected as representatives of widely used machine learning and statistical technique respectively, and a hybrid method, the combination of ANNs and WMA are introduced. The fourth section describes the four data sources used in the study, namely mobile phone network (MPN), bus-based GPS (bGPS), Inductive Loop Detector (ILD) and Automatic Number Plate Recognition (ANPR), where ANPR data are set as the ground truth. The performance of data fusion using three data sources is quantified according to its estimation accuracy followed by a discussion on the data source inputs and the merits and limitations of data fusion techniques.

BACKGROUND

A number of data sources have been used for travel time estimation, such as moving car observer data (6), the probe vehicle location data extracted from Global Navigation Satellite Systems such as GPS (7), mobile phone data (8), Automatic Number Plate Recognition (ANPR) system data (9) and flow and occupancy data from ILD (10). However, every data source has inherent biases and limitations, such as the limited sample size for Moving Car Observer (11), low polling frequency for ILD (12), the low penetration and map-matching accuracy for probe vehicle techniques (13), and the false displacement problem for the mobile phone network (14). These source-specific errors can have an impact on the accuracy of travel time estimation.

Multi-sensor data fusion technique enables to combine the heterogeneous sensors through the process of fusion, which aims to compensate for the shortcomings of individual sensor sources and therefore increase confidence, robustness and spatial coverage of the input of estimation (15). Combining multiple sensor data has several potential advantages over using a single source of data. First, different types of sensors confirming the same output can increase confidence and reduce ambiguity. Second, the same traffic state is recorded by different sensors in the form of different variables and these independent observations can enhance the reliability of measurements. Furthermore, mutual complementarity can be achieved by fusing multiple data
sources with different spatial and temporal coverage and thus increase the robustness as well as the spatial and temporal range of travel time estimation (16). For example, mobile phone has a high market penetration and thus have the advantage of wide spatial coverage. This wide spatial coverage can help to estimate the travel time on corridors without ILD. Conversely, ILD can provide accurate traffic flow information to compensate the low accuracy of mobile phone data. Recently, some researchers have attempted to explore the application of bus-based GPS data (17, 18, 19). Bus-based GPS data have the advantages of good spatial coverage and low unit cost, and is hence a potential input for travel time estimation. However, as with other single data sources, bus-based GPS data have some drawbacks, such as small sample size and biased data (as buses sometimes uses exclusive bus lane and travel faster than general traffic, but incur additional delays at bus stops). One key issue of the use of bus-based GPS data for travel time estimation is that bus-based GPS data represent a specific sub-population, i.e. buses, of general traffic. To overcome the sub-population bias, one feasible solution is to fuse bus data with data from multiple sensor types.

Some research have already shown that fusing two data sources by multi-sensor fusion techniques can produce more accurate travel time estimates (16, 20, 21, 22). However, to date there has been little research investigating the contribution of individual sources to the quality of the final estimate or how this varies according to source-specific data quality. In fact, it is reasonable to assume that the accuracy of individual data sources will influence the accuracy of the fused travel time estimates. In this context, this paper focuses on the question -- is more always better? If a number of data sources are available, should one use all available data sources or should one be selective?

METHODOLOGY

In this paper, three different data sources (MPN, bGPS, and ILD) of varying characteristics and quality are combined using three different data fusion techniques of varying complexity. Both the data sources and the fusion methods are representative of current practice. This section introduces the sensor fusion approaches used in this study.

Artificial Neural Networks

Artificial neural networks (ANNs) are a family of machine learning methods inspired by emulating the structures of biological networks, generally presented as a system of connected neurons and multi-layers of processing units (23). They have the advantages of dealing with complex linear and nonlinear problem in which the precise interrelationships among elements are not well understood and defined (24). ANNs techniques have been widely used in the sensor fusion literature both within transport and more widely (25, 26, 27, 28).

Various ANNs topologies have been applied to estimate travel time, such as fuzzy neural networks (29), probabilistic networks (30), feed-forward networks (31), recurrent neural network (32) and counter propagation neural network (33). Among the various ANNs topologies, Recurrent Neural Networks (RNNs) models are dynamic networks with internal feedbacks that enable the learning of complex temporal patterns. RNNs have three layers; an input layer, a hidden layer and an output layer, and all layers are fully connected. RNNs have been shown to be well suited to the analysis of times series data including the treatment of seasonal and other temporal structure (34, 35) and a number of researchers have used RNNs techniques for travel time estimation (27, 32). RNNs are thus selected as a representative of the wider class of
machine learning techniques used for sensor fusion in the context of travel time estimation.

**Weighted Mean Approach**

The Weighted Mean Approach (WMA) is a very simple and widely used statistical technique for sensor fusion in which specific weights can be assigned to the various data sources \((36)\). These weights are calculated to reflect the reliability of each data source, so that more reliable sources have greater influence on the final fused estimate. The WMA has been used by a number of researchers for travel time estimation \((21, 37, 38)\).

In this paper, three weighting schemes are compared. Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) are commonly used metrics to quality estimation accuracy. Thus, two weight scenarios are calculated by the inverse of MAPE and the inverse of MSE respectively. The third weighting scheme is that suggested by Choi and Chung \((21)\) which incorporates sample size information. Three weight scenarios are mathematically summarised as below.

Weight scheme 1 (w1): the inverse of MAPE

\[
W_j = \frac{1}{MAPE_j}
\]

(1)

Weight scheme 2 (w2): the inverse of the Mean Squared Error (MSE)

\[
W_j = \frac{1}{MSE_j}
\]

(2)

Weight scenario 3 (w3): sample size divided by the square of the standard deviation

\[
W_j = \frac{n_j}{s_j^2}, j = 1, ..., N
\]

(3)

where \(s_j\) is a standard deviation and \(n_j\) is the sample size of the \(j^{th}\) source. The sample standard deviation \(s_i\) can be calculated by the equation

\[
s_j = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}
\]

(4)

where

- \(n\) is the sample size
- \(x_i\) is the \(i^{th}\) sample value
- \(\bar{x}\) is the mean of sample values
- \(N\) is the number of data sources
- \(W_j\) is the weights of \(i^{th}\) data sources and \(\sum_{j=1}^{N} W_j = 1\)

**Hybrid Method**

In addition to using ANNs and WMA individually, we also use a hybrid method based on combining these two approaches. WMA has the constraints of fusing same type of independent variable to estimate the dependent variable. For example, provided with data from bus-based
GPS, mobile phone and ILD, we can only use bus-based GPS data and mobile phone data to estimate travel time by WMA, as the same travel time variable can be got from these two datasets, while ILD data who gives the traffic flow variable cannot be used directly without converting traffic flow to travel time. ANNs are effective machine learning tools to establish the relationship among different independent variables and dependent variables. With the contribution of ANNs, all traffic variables firstly can be converted into travel time. WMA plays an important role to assign more weights to the more accurate data sources and less weights to inaccurate data. Fusing the output from ANNs by WMA tends to be more powerful than the individual method.

The general process of can be summarised to three phases: firstly, sampling and cleaning the raw traffic data sources; secondly, estimating travel time using ANNs; finally, fusing the estimated travel time output from ANNs by WMA.

Quantification of Estimation Accuracy

The accuracy of the estimation is measured using four metrics: Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and Root Mean Squared Percentage Error (RMSPE).

Usually, the MPE is the average of percentage errors and measures the existence of bias in the estimation. MAPE further measures the average magnitude of the errors by setting absolute average errors without considering the direction. Apart from MPE and MAPE, a linear score which weights all the individual difference equally, a more common measure is RMSE. Since the errors are square rooted before average, RMSE assigns a relatively high weights to large errors. Compared to the MAPE, RMSE amplifies and severely punishes large errors. RMSPE provides the same properties as the RMSE, but is expressed as percent (38). Every performance criterion has their own advantages and limitations, and using all these criteria can contribute to a more synthetically evaluation of different methods. The equations of these four metrics are shown below.

\[
MPE = 100 \times \frac{1}{N} \sum_{n=1}^{N} \frac{(x_n - \hat{x}_n)}{x_n}
\]  

\[
MAPE = 100 \times \frac{1}{N} \sum_{n=1}^{N} \frac{|x_n - \hat{x}_n|}{x_n}
\]  

\[
RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (x_n - \hat{x}_n)^2}
\]  

\[
RMSPE = 100 \times \sqrt{\frac{1}{N} \sum_{n=1}^{N} \frac{(x_n - \hat{x}_n)^2}{x_n^2}}
\]

where

- \(N\) is the total number of time intervals
- \(x_n\) is the \(n^{th}\) observed travel time during the evaluation time period
- \(\hat{x}_n\) is the \(n^{th}\) estimated travel time during the evaluation time period
DATA DESCRIPTION

ANPR Data
The measurements of link travel time using as ground truth in this study are based on ANPR camera data, which is obtained from the Transport for London’s (TfL) London Congestion Analysis Project (LCAP). The ANPR data are cleaned by TfL using the overtaking rule method (39). An ANPR camera located at the start and the end of the link records the vehicle registration number and the time stamp of passing vehicles, while an external system measures the travel time using the corresponding arrival time and departure time. The cleaned average link travel time, at 5-minute intervals from 17th Feb to 27th Feb 2015 is provided on the associated link, among which LCAP 2509, 1917.38 meters in length, and LCAP 2511, 1969.24 meters in length, of A501 road that serves as central London’s major corridor are used in this research. These two links are located in same road in different directions with 7 bus stops respectively. But the traffic conditions and traffic compositions are quite different. According to the travel time pattern from ANPR data, LCAP 2509 has more serious congestion than that of LCAP 2509, while the proportion of buses on LCAP 2511 tends to larger than that of LCAP 2509 in the light of the evidence of less bus travel time from bGPS data on LCAP 2509. The locations of two links, LCAP 2509 (northeast bound) and LCAP 2511 (southwest bound), are shown in (Figure 1).

ILD Data
Single Inductive Loop Detectors are widely used for providing inputs to the SCOOT traffic control system (40). They report vehicles presence or absence (0/1 values) at 4Hz at the fixed location. Traffic variables such as flow and occupancy can be calculated from the reported data.
(41). The ILDs in corresponding LCAP links can be positioned according to their longitudes and latitudes. There are 20 detectors in the LCAP link 2509 and 21 detectors in the LCAP link 2511. In order to guarantee the initial quality of data, Robinson Daily Statistics Algorithm (DSA) test was applied to examine the working state of detectors (42). According to results of DSA cleaning, one detector of LCAP 2511 fails to meet the requirements of DSA test and therefore is excluded from the analysis, while others are remained as cleaned traffic flow for further travel time estimation. ILDs data in the 5-minutes interval from 7:00 to 19:55 during the period of 17th Feb-27th Feb 2015 are available in this research.

**Mobile Phone Data**

The MPN data used in this study was provided by a commercial supplier in the form of direct estimates of travel time on the segmented links, grouped into 4 pseudo-modal categories: static, walking, moving (car, bus, freight, etc.) and rail. Only the moving group is used in this paper. Every LCAP link has several segmented links. Adding up travel time of segmented links to obtain the corresponding LCAP links is the main idea to process the mobile phone data. Five days data from 23rd Feb to 27th Feb 2015 are available in this research. These data are extracted in 5-minute intervals from 7:00 to 19:55 every day and thus we have 156 samples per day and 780 samples in total.

The travel time sourced from MPN data are significantly different from the corresponding ‘true’ travel time from ANPR on both two links, as shown in (Figure 2). The MAPE is 152% on LCAP 2509 and 62% on LCAP 2511 respectively. The quality of mobile phone data on LCAP 2509 is better than that of LCAP 2511. These differences are statistically significant at the 1% level (using a suitable nonparametric (Friedman) test). A number of reasons may account for these differences including in low sampling rates, spatial imprecision in positioning leading to errors in map matching and errors in modal discrimination.
FIGURE 2 Example of scatterplots and travel time patterns on LCAP 2509 and LCAP 2511
**Bus-based GPS Data (bGPS)**

The bGPS data are extracted from Transport for London (TfL)’s GPS-enhanced Automated Vehicle Location System, which is used to improve traffic signal control operation and bus fleet management. The iBus system operates on over 8500 buses, providing the real-time GPS location and signage, throughout London \((43)\). bGPS data are extracted in 5-minute intervals from 7:00 to 19:55 every weekday from 17\textsuperscript{th} Feb to 27\textsuperscript{th} Feb 2015, and thus we have 156 samples per day and 1404 samples in total, same with that of ILDs and ANPR.

The iBus system provides bGPS data with traffic variables such as the average bus speed on route for traffic control and management. In addition, the iBus system provides information on the location of buses from which estimates of journey duration can be derived. The link travel time is estimated by adding up the travel time of segmented links, in a manner similar to the pre-process of the MPN data. As one would expect, bus travel time is also significantly different at the 1\% level (using a suitable nonparametric (Friedman) test), and generally larger, than the travel time of the general traffic stream as measured by ANPR.

Comparing the MPN and bGPS data, it is clear that both are substantially different from ANPR, reflecting both differences in the source technologies and differences between the behavior of the general traffic stream and the sub-populations comprising bus and mobile phone users. Interestingly, there is a high correlation of MPN and bGPS data in both links, which may reflect the fact that many of the mobile phones contributing data to the MPN data source are in fact located on bus passengers. It is also notable that the differences between MPN and bGPS data and the ANPR ground truth data differ significantly as between the two links. On LCAP 2509 MPN and bGPS generally over-estimate the ANPR-based travel time, whereas on LCAP 2511 the tendency is to under-estimate the ANPR-based travel time. This may reflect the influence of different traffic compositions and traffic conditions on these two links.

**EXPERIMENTAL RESULTS AND ANALYSIS**

This section presents the results of the data fusion analysis using ANNs, WMA and hybrid method respectively. We divide the data sample into the training dataset and test dataset, accounting for 70\% and 30\% respectively. The training dataset is used to train ANNs or calculate the weights in WMA, while the test dataset is applied to quantify the out-of-sample accuracy of travel time estimation for the calibrated method.

**Data Fusion Using ANNs**

ANNs Framework

In order to implement the ANNs to this research, the framework shown in (Figure 3) is used.
As for one data sources, traffic flow from ILD data, and travel time from mobile phone and bGPS data, are used as inputs respectively to estimate travel time by the ANNs method. Then different combination of two and three data sources are fused together to estimate travel time. The final accuracy is quantified by MPE, MAPE, RMSE and RMSPE.

**Results and Discussion**

With trial and error method, the travel time results from ANNs with optimised parameters are presented. Overall, the recurrent neural network gives accurate travel time estimates based on different data inputs on both LCAP 2509 and LCAP 2511. The detailed quantification of accuracy is shown in (Table 1).
As can be seen in Table 1, in general, the ANNs provide accurate travel time estimates in the light of MAPE and RMSE. It is obvious that the performances using one data input override that of accuracy from using two and three data inputs according to MAPE criteria. One possible reason is that the patterns of travel time from mobile phone and bGPS (Figure 2), as well as the variation of flows from detectors, are quite different, and at the same time, with large errors compared to ‘ground truth’ from ANPR. Fusing them together using ANNs with feedback loop may add extra noise to the estimated results.

**Data Fusion Using WMA**

**WMA Framework**

In order to implement the WMA, same traffic variables with that of ‘ground truth’ are needed as the input of the WMA. We can get the travel time variable from ‘ground truth’ ANPR data, bGPS data and mobile phone data, while get traffic flow from ILD. Thus, only bGPS and mobile phone data are fused based on three weight scenarios. The framework is shown in (Figure 4).
Results and Discussion

The bGPS and mobile phone data are fused with different weights. The results are shown in (Table 2).
<table>
<thead>
<tr>
<th></th>
<th>bGPS + Mobile Phone</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>LCAP 2509</strong></td>
<td></td>
</tr>
<tr>
<td>w1 (the inverse of MAPE)</td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-131.92</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>135.59</td>
</tr>
<tr>
<td>RMSE</td>
<td>329.26</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>164.08</td>
</tr>
<tr>
<td>w2 (the inverse of MSE)</td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-130.40</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>134.28</td>
</tr>
<tr>
<td>RMSE</td>
<td>325.99</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>162.84</td>
</tr>
<tr>
<td>w3 (w_i = n_i / s_i)</td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-125.34</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td><strong>130.09</strong></td>
</tr>
<tr>
<td>RMSE</td>
<td>316.16</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>159.03</td>
</tr>
<tr>
<td><strong>LCAP 2511</strong></td>
<td></td>
</tr>
<tr>
<td>w1 (the inverse of MAPE)</td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-49.93</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td><strong>51.89</strong></td>
</tr>
<tr>
<td>RMSE</td>
<td>218.61</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>64.58</td>
</tr>
<tr>
<td>w2 (the inverse of MSE)</td>
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<tr>
<td>MPE (%)</td>
<td>-50.73</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>52.60</td>
</tr>
<tr>
<td>RMSE</td>
<td>220.59</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>65.56</td>
</tr>
<tr>
<td>w3 (w_i = n_i / s_i)</td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-52.08</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>54.01</td>
</tr>
<tr>
<td>RMSE</td>
<td>225.33</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>67.49</td>
</tr>
</tbody>
</table>
As can be seen in (Table 2), the performance of different weight scenarios is varied and depends on the statistical information in both training and test dataset. In addition, fusing two different data source by WMA does not necessarily contribute to better results compared to the performance based on single data input. We can also conclude that the performance of ANNs is obviously better than that of the WMA. The reason why WMA does not output accurate travel time estimates probably due to the some dependences between bGPS and mobile phone data. The example of scatterplots showing this dependency is shown in (Figure 2). The patterns of mobile phone and bGPS data are quite similar, which lead to correlations among two different datasets. The performance of LCAP 2511 is better than LCAP 2509, same with the results from ANNs data fusion, which indicates that the quality of data inputs have an impact on the performance of data fusion.

**Data Fusion Using the Hybrid Method**

*Hybrid Method Framework*

The hybrid method is the combination of ANNs and WMA. This method estimates the travel time by ANNs, and then fuses these ANNs outputs by WMA model to produce the final travel time estimates. The framework is shown in (Figure 5).

![Diagram of Hybrid Method Framework](image)

**FIGURE 5 Framework of the hybrid method**

*Results and Discussion*

The weights of WMA are calculated according to the MAPE, MSE and $s^2$ from training data of ANNs. The results from LCAP 2509 and LCAP 2511 are shown in (Table 3).
TABLE 3 Summary of the Hybrid Method Performance on LCAP 2509 and LCAP 2511

<table>
<thead>
<tr>
<th></th>
<th>One Data Source</th>
<th>Two Data Sources</th>
<th>Three Data Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ILD</td>
<td>MPN</td>
<td>bGPS</td>
</tr>
<tr>
<td><strong>LCAP 2509</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>w1 (the inverse of MAPE)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-2.43</td>
<td>0.15</td>
<td>-0.46</td>
</tr>
<tr>
<td>RMSE</td>
<td>47.65</td>
<td>47.53</td>
<td>45.88</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>16.32</td>
<td>14.93</td>
<td>12.99</td>
</tr>
<tr>
<td><strong>w2 (the inverse of MSE)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-2.43</td>
<td>0.15</td>
<td>-0.46</td>
</tr>
<tr>
<td>RMSE</td>
<td>47.65</td>
<td>47.53</td>
<td>45.88</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>16.32</td>
<td>14.93</td>
<td>12.99</td>
</tr>
<tr>
<td><strong>w3 (<strong>w</strong>1 = n_1/n_i)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-2.43</td>
<td>0.15</td>
<td>-0.46</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>11.12</td>
<td>10.17</td>
<td>9.76</td>
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<tr>
<td>RMSE</td>
<td>47.65</td>
<td>47.53</td>
<td>45.88</td>
</tr>
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<td>16.32</td>
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</tr>
<tr>
<td><strong>LCAP 2511</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>w1 (the inverse of MAPE)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-1.22</td>
<td>-1.38</td>
<td>-1.56</td>
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<tr>
<td>MAPE (%)</td>
<td>7.33</td>
<td>7.22</td>
<td>7.19</td>
</tr>
<tr>
<td>RMSE</td>
<td>53.23</td>
<td>40.42</td>
<td>50.91</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>9.58</td>
<td>9.33</td>
<td>9.48</td>
</tr>
<tr>
<td><strong>w2 (the inverse of MSE)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-1.22</td>
<td>-1.38</td>
<td>-1.56</td>
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<tr>
<td>MAPE (%)</td>
<td>7.33</td>
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<td>9.58</td>
<td>9.33</td>
<td>9.48</td>
</tr>
<tr>
<td><strong>w3 (<strong>w</strong>1 = n_1/n_i)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPE (%)</td>
<td>-1.22</td>
<td>-1.38</td>
<td>-1.56</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>7.33</td>
<td>7.22</td>
<td>7.19</td>
</tr>
<tr>
<td>RMSE</td>
<td>53.23</td>
<td>40.42</td>
<td>50.91</td>
</tr>
<tr>
<td>RMSPE (%)</td>
<td>9.58</td>
<td>9.33</td>
<td>9.48</td>
</tr>
</tbody>
</table>
Among three weight scenarios of the hybrid method, the inverse of MAPE gives the best estimates, and the main reason may come from the consistent performance on the training dataset and test dataset. The data fusion techniques are vital to estimate accurate travel time. And more advanced data fusion techniques can also help to improve the estimation accuracy and reliability. Combining WMA and ANNs can take the advantages of both methods to compensate for the distortion caused by time lag and therefore reduce the spacing error from ILD and mobile phone data. It is obvious that all of the estimates from the hybrid method are accurate than that of ANNs and WMA. The possible reason is that hybrid method gives more weights to the accurate data and less weights to the inaccurate data. In addition, the underestimation and overestimation parts in ANNs can be offset by WMA to achieve a more accurate results than the results from using ANNs or WMA only.

In contrast with WMA and ANNs that one input is better than fusing two or three, using hybrid method to fuse multiple data sources can improve the accuracy of estimates compared to using only one data input. To be specific, fusing bGPS data with ILD data can reduce one third MAPE of fusing single bGPS or ILD data on LCAP 2509 while reduce half MAPE on LCAP 2511.

Comparing the results based on fusing two data sources and three data sources, we can find that fusing some specific two data sources is better than fusing three more data sources together. The combination of bGPS and ILD data as inputs estimates the most accurate results, superior than that of three data sources. This can be ascribed to the correlations among different data sources, for example, the correlation between bGPS and mobile phone data can reduce the accuracy of travel time estimates.

The quality of data inputs that LCAP 2511 is better than LCAP 2509 leads to more accurate estimates for LCAP 2511 than that of LCAP 2509. It indicates that the quality of data input can influence on the outputs no matter which methods are selected.

CONCLUSION
The results presented in this paper show that the final accuracy of travel time estimation depends on the reliability of individual data sources and the characteristics of the sensor fusion techniques used. The hybrid method outperforms WMA and ANNs to fuse multiple data resources, and outputs more accurate travel time estimation in this research. However, fusing more data sources does not necessarily improve the quality of the final estimate. The results show that fusing highly correlated data sources can lead to a worse result. The results also show that although bGPS data is inherently based on just a sub-population of the general traffic stream with markedly different behavior to that of the general stream, when bGPS is combined with ILD data from the general traffic stream, reasonable estimates of general traffic stream travel time can be obtained.

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REFERENCES


