

Estimation of Statistical Traffic Data for Navigation Systems

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In Japan, more users have been able to make use of traffic information service in real time as VICS (Vehicle Information and Communication System) and navigation systems have been deployed. However, navigation systems can not always guide drivers on appropriate routes using only travel time data as they are because of the problems of accuracy and quantity. Therefore, this paper proposes estimation methods of statistical traffic data for an appropriate route search in navigation system. It includes several ideas for making the statistical traffic data more accurate. This paper describes and evaluates the algorithms for the estimation.

Keywords: Travel time, Traffic congestion, Statistics, Estimation, Navigation system, Route search

1. Introduction

Since 1996 when the use of VICS (Vehicle Information and Communication System) [1] started in Japan, as service areas have been extended and navigation systems equipped with VICS have penetrated the market, more users have been able to access traffic information in real time [2]. On the other hand, in traffic information centers, information accuracy has been improved and the information area has been extended by the efficient use of traffic detector data [3][4]. So traffic information service has become more convenient. One of the uses of traffic information in navigation systems is a dynamic route search avoiding traffic congestion. It sets a weight on each link according to its travel time and calculates the route which leads to the destination by the shortest time [5]. Another function is prediction of an arrival time at the destination.

VICS traffic information is mostly based on the data measured by vehicle detectors on roads [4]. So there are two problems for a dynamic route search in navigation system.

One is the problem caused by data of presence type vehicle detectors such as ultrasonic vehicle detectors. Usually the travel times of links are estimated using their data and we should pay attention to the following points as to travel time accuracy.

- (1) Travel speed is estimated using traffic volume and time occupancy measured by vehicle detectors. Thus it may include an estimation error.
- (2) Travel time is estimated by expanding data measured at one point of the road into the link. Thus it may include an estimation error.

- (3) Measured data detecting an illegal parked vehicle in the measuring area may negatively influence travel time estimation.

These problems influence the accuracy of travel times, so navigation systems sometimes cannot actually guide drivers to the fastest routes.

Another problem is that the quantity of current traffic data is still not necessarily sufficient for an appropriate route search, because priority for road sensor installation is given to expressways and major arterial roads according to cost effectiveness for infrastructure. Figure 1 shows the links on which actual traffic information is provided from VICS. Bold lines along roads show traffic congestion and you can see approximately which links traffic information is provided on. The quantity of traffic information in a suburban district tends to be less than in an urban district.

On the other hand, algorithms for route search are usually based on the Dijkstra method [6], because the method can efficiently calculate a route of good quality. It searches all links from departure to destination and finds the fastest route. When travel time on a link is provided, the navigation system makes use of it, but when it is not provided, the navigation system makes use of average speed data instead. The data is static and it is investigated in advance. Therefore, the more links whose travel times are provided, the better quality route is given. Actually it is not possible that travel times in all links are provided. The links whose travel times are provided need to be as many as possible in the areas where frequent traffic congestion makes the static traffic data quite different, such as in the Tokyo metropolitan area. But actually there are not necessarily sufficient links whose travel times are provided, and navigation systems sometimes cannot guide drivers to the fastest routes.

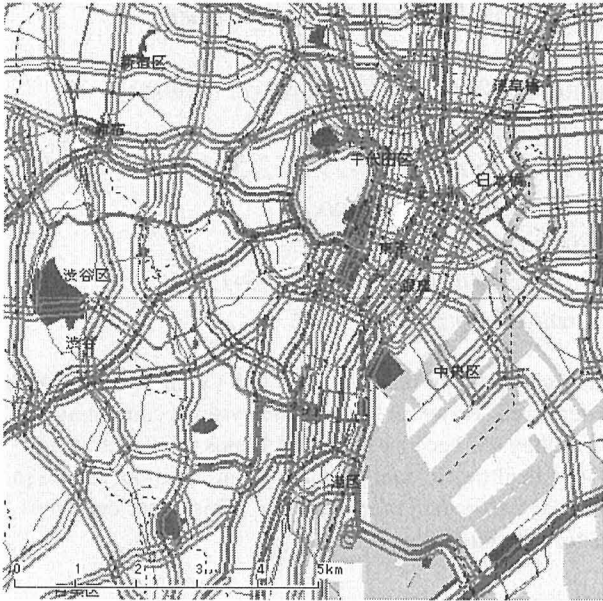


Figure 1(a). Traffic information in an urban district in the Tokyo metropolitan area

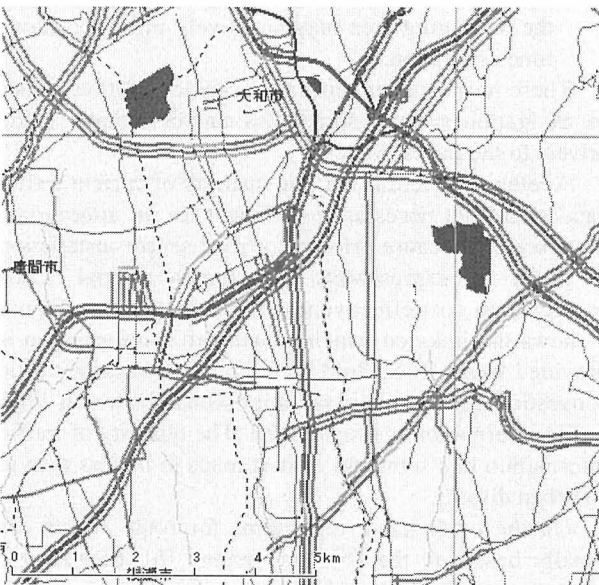


Figure 1(b). Traffic information in a suburban district in the Tokyo metropolitan area

One of the means for overcoming these problems is a probe car system, which is also called a floating car system. Currently many such systems are in an experimental phase [7][8]. Some of them have already been launched [9][10]. But it may take a long time for them to be really practical and useful because a large number of probe cars are needed in order to provide drivers with traffic information for many links throughout Japan at all times.

Therefore, using the VICS information which is currently most available and most useful, we studied on estimation method for statistical traffic data. The method

improves information accuracy by statistical processing and increases the amount of information by estimating traffic data on links whose traffic information is not provided (which are called “information-unprovided links” below) using the traffic data of neighboring links. The statistical traffic data is installed in navigation systems and is used for a route search.

2. Estimation of statistical traffic data

2.1. Classification of statistical traffic data

Common experience holds that traffic conditions differ on weekdays and holidays. But our analysis shows that real traffic data on different dates is more similar how they are classified by day type. In the analysis, we used one year of stored traffic data on expressways and arterial roads in the Tokyo metropolitan area, except unusual dates (“Golden Week” which is a series of consecutive holidays from the end of April to the beginning of May, the week of the “Bon festival” in August, and the end and the beginning of year).

Figure 2 shows the flow of processing for the analysis. It may be thought that the classification set is determined by the cluster analysis. But we nominated several day-types (e.g. each day of the week and weekdays / holidays) based on our experience and evaluated each similarity relatively, because we have to avoid data including incidents such as traffic accidents. Inputting the date list for the day-type and the traffic data, we analyze the data with the following steps.

- (i) The following on a link are extracted from the traffic data and the correlation coefficient between them is calculated.
 - (a) Time series travel times on date i among the listed dates for the day-type
 - (b) Complement of the date i , which corresponds to the average of time series travel times on other dates
- (ii) Applying step (i) on all object links, we calculate correlation coefficient on each link. The correlation coefficient \hat{r}_i on the date is calculated by averaging all of them and it is expressed by equation (3). Here the links whose correlation coefficient cannot be calculated are excluded from the object links (e.g. information-unprovided links and the links whose fixed traffic data is provided all day).
- (iii) Applying step (i) and (ii) on all dates involved in the day-type, we calculate correlation coefficient on each date. The correlation coefficient \hat{r} on the day-type is calculated by averaging all of them and it is expressed by equation (4).
- (iv) Step (i) to (iii) are carried out on all of the day-types, and correlation coefficient is calculated each day-type.

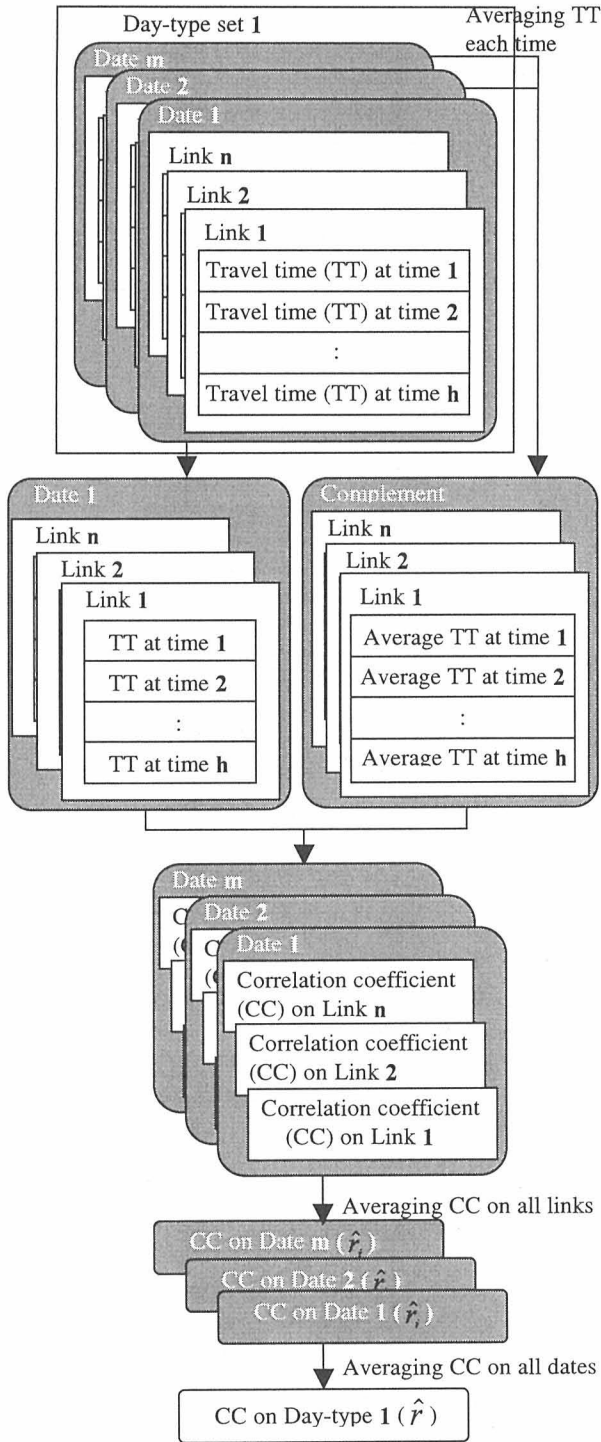


Figure 2. Flow of classification analysis

We evaluated the similarity of classifications by comparing their average correlation coefficients as calculated by the analysis. This time we have a large amount of calculation, because the targets are about 11,000 links in the Tokyo metropolitan area and the data is one year of stored traffic data including 288 data per link per day. Therefore, we substituted \hat{r} in equation (4) for r in equation (2) which should be calculated

fundamentally. The r is calculated by averaging the $r_{i,j}$ of all combinational dates i and j . The \hat{r} is calculated by averaging the \hat{r}_i of all object dates.

$$r_{i,j} = \frac{1}{n} \sum_{k=1}^n \frac{\sum_t (T_{i,k,t} - \bar{T}_{i,k})(T_{j,k,t} - \bar{T}_{j,k})}{\sqrt{\sum_t (T_{i,k,t} - \bar{T}_{i,k})^2} \sqrt{\sum_t (T_{j,k,t} - \bar{T}_{j,k})^2}} \quad (1)$$

$$r = \frac{2}{m(m-1)} \sum_{i=1}^m \sum_{j=1}^m r_{i,j} \{i, j \mid i < j\} \quad (2)$$

$$\hat{r}_i = \frac{1}{n} \sum_{k=1}^n \frac{\sum_t (T_{i,k,t} - \bar{T}_{i,k})(T_{i,k,t}^C - \bar{T}_{i,k}^C)}{\sqrt{\sum_t (T_{i,k,t} - \bar{T}_{i,k})^2} \sqrt{\sum_t (T_{i,k,t}^C - \bar{T}_{i,k}^C)^2}} \quad (3)$$

$$\hat{r} = \frac{1}{m} \sum_{i=1}^m \hat{r}_i \quad (4)$$

$$T_{i,k,t}^C = \frac{1}{m-1} \sum_{j=1}^m T_{j,k,t} \{i, j \mid i \neq j\} \quad (5)$$

$r_{i,j}$: Average of each link's correlation coefficient between date i and date j

$T_{i,k,t}$: Travel time of the link k at time t on date i

$\bar{T}_{i,k}$: Average of $T_{i,k,t}$ on a day

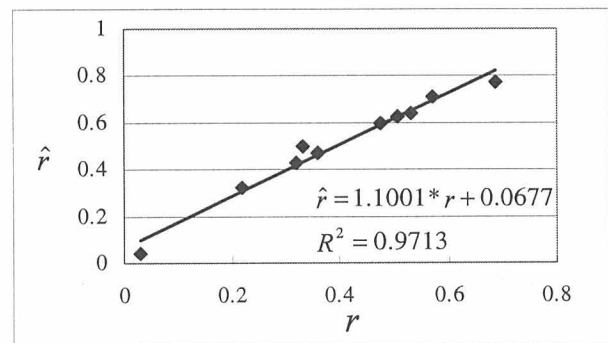
\hat{r}_i : Average of each link's correlation coefficient between date i and its complementary dates

$T_{i,k,t}^C$: Average travel time of the link k at time t on the complementary dates of date i (equation (5))

$\bar{T}_{i,k}^C$: Average of $T_{i,k,t}^C$ on a day

m : number of object dates

n : number of object links


 Figure 3. Correlation between r and \hat{r}

Here we compared r and \hat{r} using travel time data for four days on 10 links for random sampling. As shown in Figure 3 their correlation was strongly positive, and so this substitution was certainly effective.

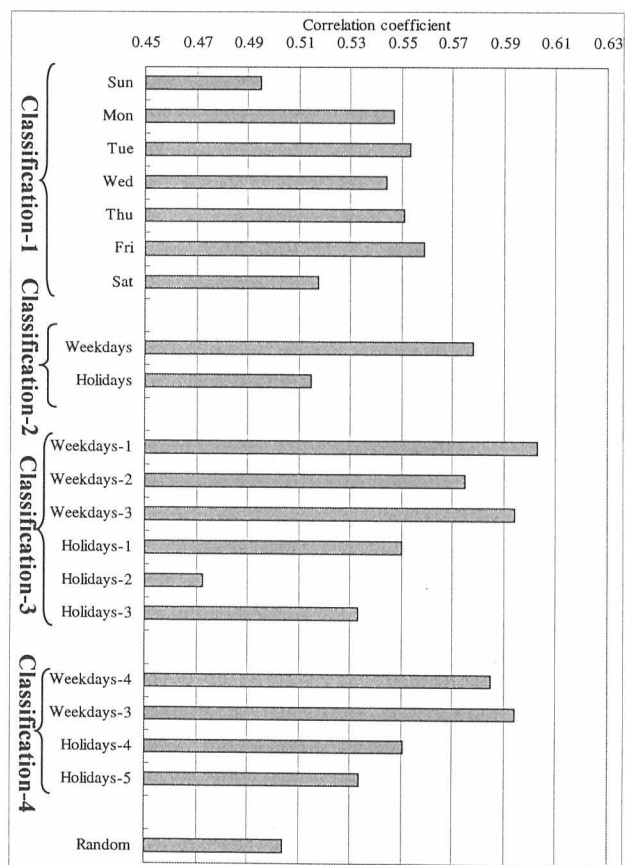
In a link, travel time at a time has something to do with the travel times before and after the time and travel times at a near time are not independent. But travel times have the characteristic of varying at a daily cycle. So we pay attention to time series travel time set on a date T_i , T_j (i, j : date) and the travel times $T_i(t)$, $T_j(t)$ at the time t are correlative each other. Applying this idea, we can compare the correlation coefficient of each day-type.

Next we evaluated the actual similarity of each classification. First we prepared three classifications 1 to 3 for the evaluation, as described in Table 1. They were assumed to be similar from our experience. In classification 1, dates are classified into seven types, one for each day of the week. In classification 2, they are classified into two types, weekdays and holidays. This classification may be widely accepted from common experience. In classification 3, there are six types. This idea is based on the influence of consecutive holidays. Here, in order to relatively evaluate the level of their similarity, we prepared a random classification in which every day of the week is assigned at random. The average correlation coefficients of each classification are shown in Figure 4. Evaluating these results as a whole, we found the correlation of the different classifications to rank, from best to worst, classification 3, classification 2, classification 1, and random classification.

The correlation of Holidays-2 in classification 3 was bad, because there were far fewer target dates than for the other types (only six or seven days a year). Therefore, we considered the target dates were assigned for Holidays-1 and Holidays-3, and we newly set Holidays-4 and Holidays-5 as alternatives to Holidays-1 to Holidays-3. With the precondition that statistical traffic data is installed on a storage medium such as DVD-ROM or HDD in a navigation system, there may not be enough free area in the medium, because the sizes of data for detailed maps and places retrieval have increased recently. Thus we must reduce the amount of data by reducing the number of weekday classifications. From our experience we had the idea that traffic conditions on Fridays tended to be much different from other weekdays. Therefore, we newly defined Weekdays-4 as the union of Weekdays-1 and Weekdays-2 and we set classification 4, which was composed of Weekdays-3, Weekdays-4, Holidays-4 and Holidays-5 (Details of each type are shown in Table 1). From the evaluation of average correlation coefficient, we found the performance of classification 4 was approximately equal to that of classification 3. In the following we treat traffic data statistically based on the classification 4.

Table 1. Classification of day types

Classifications	Day-types	Notes
1	Sundays	
	Mondays	
	Tuesdays	
	Wednesdays	
	Thursdays	
	Fridays	
	Saturdays	
2	Weekdays	Monday to Friday
	Holidays	Saturday, Sunday, and national holidays
3	Weekdays-1	Monday
	Weekdays-2	Tuesday to Thursday
	Weekdays-3	Friday
	Holidays-1	Saturday and first day of consecutive holidays
	Holidays-2	middle of consecutive holidays
	Holidays-3	Sunday and last of consecutive holidays
4	Weekdays-4	Monday to Thursday
	Weekdays-3	Friday
	Holidays-4	Saturday and first day of consecutive holidays
	Holidays-5	Sunday and remainder of consecutive holidays


Figure 4. Correlation coefficient by classifications

2.2. Improvement of estimation accuracy by statistical processing

As described above, we decided to treat traffic data statistically in order to improve the accuracy of traffic information. The statistical traffic data for navigation systems needs to be accurate enough to express usual traffic conditions with adequate filtering of unusual data based on sudden incidents such as traffic accidents. This paragraph describes the methods for adequately filtering unusual traffic data.

First, the following three types of unusual data are defined from the analysis of real traffic data.

Type I: Traffic data such that travel speed is too fast for the road. The causes may be error of estimated average travel speed using the data from a vehicle detector, and error from expanding data measured on a point of the road into the link.

Type II: Traffic data such that traffic congestion is generated too frequently. The causes may be sensor's detection of an illegal parked vehicle in addition to the causes of Type I.

Type III: This is atypical traffic data (e.g. incidents such as traffic accidents). The data of this type may be generated because Type II causes happen suddenly. But unusual traffic conditions caused by traffic accidents or other incidents may also cause the data of this type.

Next, we describe the method for detecting unusual traffic data at each type.

(1) Type I

When travel speed is faster than sum of the regulation speed and a permissible speed, the traffic data is detected as Type I. The permissible speed is determined from the value, which corresponds to the 95th percentile of the speed distribution. It is determined that permissible speeds for arterial roads and expressways were respectively 30km/h and 40km/h. For example, in an expressway whose regulation speed is 60km/h, when travel speed is faster than 100km/h it is detected as Type I.

(2) Type II

When traffic congestion on a link occurs more frequently than the permissible ratio for a day, it is detected as Type II. The permissible ratio of congestion should be set so that the probability of the occurrence becomes quite low in usual traffic conditions without incidents. We set it at 80% judging from our experience. In other words, this is based on the experience that traffic congestion seldom occur for over 19 hours of 24 hour span. Actually most of the Type II data are errors made by detectors.

(3) Type III

When travel speed is quite different from that at the same time on other days of the classification, it is

detected as Type III. The permissible deviate of speed is defined as the range of normal data in the following equation.

$$\bar{X} - \alpha \cdot s_X \leq X \leq \bar{X} + \alpha \cdot s_X \quad (6)$$

\bar{X} : Average of data set X

s_X : Standard deviation of data set X

α is a predetermined parameter. X is travel speed. As the amount of the data is sufficient because of the use of classification 4 with dates classified into four types, we set α at 1.0. So the range for judging data as normal is a little narrow.

Next, the steps for filtering unusual traffic data of Type III are described.

- (i) Average \bar{X} and standard deviation s_X of data set X in a given time are calculated.
- (ii) Tentatively, the data which don't satisfy equation (6) are regarded as unusual data and the number N of the unusual data is counted up.
- (iii) The data whose deviations are the maximum of the unusual data are excluded, then the average and standard deviation of the remaining data set are calculated again by the same way as (i).
- (iv) Step (iii) is iterated until the number of excluded data is equal to N or all of the remaining data satisfy equation (6).

Table 2 shows the situation of detecting unusual traffic data of Type I and Type II in a day on 19,726 links, sampled at random. The ratios of the traffic data detected as Type I or Type II were small values, but some particular links tended to be detected more frequently. These methods for unusual data detection would contribute to the improvement of accuracy on these links. Next, Table 3 shows the situation of detecting unusual traffic data of Type III on 40 links, whose traffic conditions change considerably with the days, using one year of stored data. 21.6% of all traffic data were judged as unusual on the average, because the target links were the links whose traffic conditions changed considerably and the permissible deviate of speed was comparatively limited. As shown in Table 4, filtering of Type III might be able to reduce the standard deviation of data and contribute to improvement of the traffic data stability and accuracy.

After unusual data are excluded by these filtering methods, statistical traffic data is estimated every five minutes by averaging the remaining normal data. Therefore we can provide sufficient usual traffic data, or in other words accurate traffic data.

Table 2. Ratio of data detected as type I and type II unusual data

	Type I	Type II
Ratio of detection	0.89%	0.70%

Table 3. Ratio of data detected as type III unusual data

	Type III
Ratio of detection	21.62%

Table 4. Comparison between statistical traffic data without and with type III detection

Areas	Sample links	Average standard deviation (km/h)		Ratio of type III data
		Without detection	With detection	
A	10	5.07	2.17	22.4%
B	10	3.18	1.39	25.0%
C	10	5.46	2.09	23.7%
D	10	9.53	2.78	15.3%

2.3. Estimation of traffic data on information-unprovided links

For the purpose of increasing the amount of traffic data without spoiling its accuracy, we propose the following estimation methods.

2.3.1. Estimation from traffic congestion data (Estimation-1). Though travel time and traffic congestion data is involved in the VICS information, actually the situation of data provision differs with the links. For example, some links have both types of data and other links have one type of data. Analyzing the real VICS information, we found travel time and traffic congestion data were provided for 53% and 86% respectively of all information-provided links and traffic congestion data was provided more widely. The target traffic data for our statistical traffic data is travel time which is used for route search in navigation systems. Efficient use of traffic congestion data is indispensable for increasing the amount of traffic data. And travel time is estimated from traffic congestion data in the following.

The traffic congestion data of the VICS information is composed of congestion level, which is expressed with three levels (smooth, light congestion, and heavy congestion), and length (congestion length). In the VICS, the guideline of congestion levels is defined as shown in Table 5. Generally regulation speed of the different road types to rank, from faster to slower, Inter-city expressway, Intra-city expressway, and others. And real VICS travel speeds approximately tend to be in proportion to regulation speeds.

Therefore, we define the equation for travel speed V_c corresponding to each congestion level in the following.

$$V_c = a_c \cdot V_r + b_c \quad (c = 1, 2, 3) \quad (7)$$

$c = 1$: Smooth

$c = 2$: Light congestion

$c = 3$: Heavy congestion

where V_r is regulation speed of the link, and a_i and b_i are parameters determined for each congestion level. These parameters are determined by the method of least squares using the data of links where both travel time and traffic congestion data are provided at the same time. When a link includes sections of plural congestion levels, its travel time is calculated according to their length. The relation between congestion levels and travel speeds differs with areas, and we determined the parameters for each area. Table 6 shows samples of the travel speeds estimated from congestion levels. We can estimate travel time using the travel speed estimated by this method, and we can increase the amount of travel time data without spoiling its accuracy.

Table 5. Guideline of congestion levels in the VICS

Road types	Congestion levels	
	Light congestion	Heavy congestion
Inter-city expressway	Slower than 60 km/h	Slower than 40 km/h
Intra-city expressway	Slower than 40 km/h	Slower than 20 km/h
Others	Slower than 20 km/h	Slower than 10 km/h

Table 6. Samples of the travel speeds estimated from congestion levels (links' regulation speed is 60km/h)

Areas	Congestion levels		
	Smooth	Light congestion	Heavy congestion
A	28.3 km/h	11.2 km/h	6.3 km/h
B	43.6 km/h	16.4 km/h	6.9 km/h
C	37.4 km/h	15.4 km/h	7.6 km/h
D	51.5 km/h	28.3 km/h	14.4 km/h

2.3.2. Estimation from traffic data on neighboring links. There are some information-unprovided links whose traffic information is not provided at all as shown in Figure 1. It is very important for increasing the amount of traffic data to estimate travel times of such links somehow. Therefore we estimate travel times on information-unprovided links using traffic data on neighboring links.

(1) Estimation from traffic data on other links which belong to the same street and direction (Estimation-2)

There are not a few information-unprovided links whose traffic data is not provided partly in major roads including national roads and expressways. This

estimation method is based on the idea that traffic conditions in such links are similar to those in neighboring links, which belong to the same street and direction. As shown in Figure 5, if there are neighboring links which are satisfied with these conditions, the method estimates travel speeds and travel times of the information-unprovided links using the traffic data from neighboring links.

Here are the steps for the estimation. First, a speed ratio $R_i (= V_i / V_{r_i})$ is calculated as the ratio of travel speed V_i calculated from statistical travel times on the resource link i based on its regulation speed V_{r_i} , and the average of the speed ratios of all resource links is calculated as a speed ratio of the target link. Next, estimated travel speed on the target link is calculated as a product of its speed ratio and regulation speed, and its travel time is estimated from the estimated travel speed and link length. Speed ratio is introduced in order to cope with the situation where regulation speed sometimes differs among links.

However, when there is a bottleneck, which changes traffic conditions considerably, between the target link and the resource link, traffic data on the resource link is hardly used for estimation on the target link. The targets of this method are information-unprovided links throughout Japan, and actually it is difficult to grasp all bottlenecks, and at this time we regard an intersection crossed among major roads as a bottleneck. Also, traffic data on the resource link, which is located in predetermined distance (2 km) further, is hardly used for estimation, because traffic conditions on such a resource link may not be so similar to those on a target link.

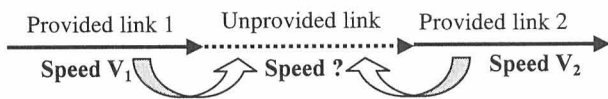


Figure 5. Concept of Estimation-2

(2) Estimation from traffic data of other links which belong to the same area and road type (Estimation-3)

The targets of this method are information-unprovided links which are not targets of Estimation-1 and 2. For example, though traffic data for Route 1 is provided, data for Route 2 is not. Such routes are widespread in Japan. This estimation method is based on the idea that traffic conditions on such links are similar to those on the links which belong to the same area (mesh) and same road type (e.g. inter-city expressways, intra-city expressways, national roads, local public roads, and so on). As shown in Figure 6, if there are links which are satisfied with these conditions, the method estimates travel speeds and travel times on the information-unprovided links using their traffic data. As to the similarity of estimated traffic data, Estimation-3 may be inferior to Estimation-2, but it may be superior to the conventional method which estimates traffic data using

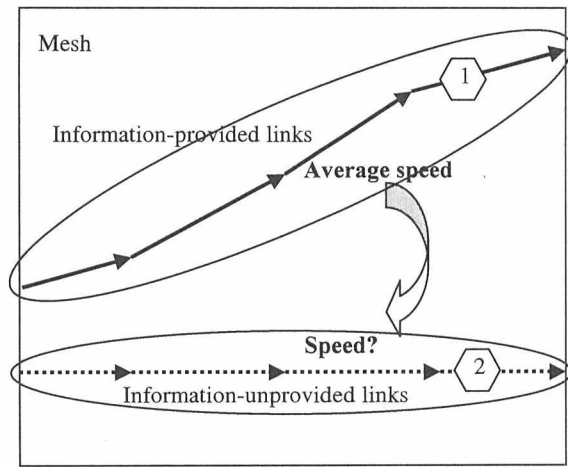


Figure 6. Concept of Estimation-3

static average speed, because we have experience that traffic conditions on information-unprovided roads tend to be as congested as neighboring roads and the similarity is remarkably comparable on every road type. Travel times on target links are estimated using the speed ratio in the same way as Estimation-2.

3. Evaluation of statistical traffic data for navigation system

3.1. Evaluation of statistically processed traffic data

We evaluated the accuracy of statistical traffic data which had been processed statistically after filtering unusual data of all types. We had driving tests on major arterial roads in northern Ibaraki Prefecture and we collected the measured travel time data as the actual values for the evaluation. Travel time data which was estimated by statistical processing and travel time data which was provided in real time from the VICS were respectively compared with the actual data, and their results are shown in Figure 7. As to accuracy, the VICS data gave a little better results, but the statistical data was by no means inferior although it is not real-time data.

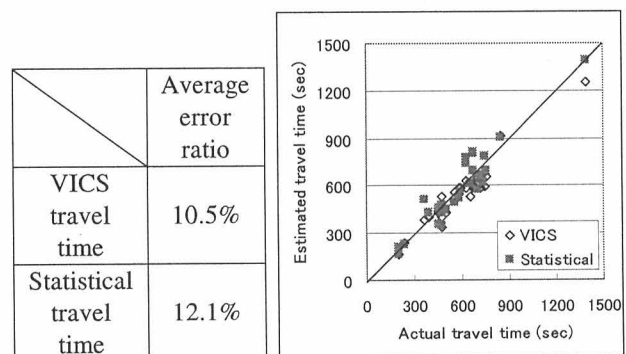


Figure 7. Comparison between statistical travel time and the VICS travel time

3.2. Evaluation of estimation method for information-unprovided links

We evaluated the effects and performance of Estimations-1, 2, and 3.

First, Figure 8 shows items of the estimation types for statistical travel time data for each of the four major metropolitan areas (10km areas). You can see the ratios of items differ with the areas. For example, in Nagoya there were 674 links whose travel time data had been provided. But there were 1,079 links whose traffic congestion data only had been provided, and so the amount of traffic data could be considerably increased by Estimation-1. Even in the suburbs of these areas, the estimation method using traffic data of neighboring links (Estimations-2 and 3) tended to increase the amount of traffic data considerably. Summing up these areas, we found conventional navigation system could use traffic data on about 5,600 links for route search. But we could accomplish a great improvement so that traffic data on about 11,400 links could be used, including the increase using the three estimation methods. From the above, these estimation methods were certainly effective for increasing the amount of traffic data.

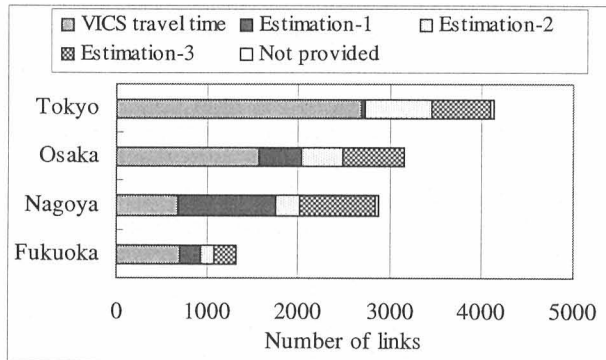


Figure 8. Items of estimation types in four major metropolitan areas

Next, we evaluated the accuracy of the travel times estimated by these methods. We used the classification 4 as classification of statistical traffic data for the evaluation. The evaluation is the same as for the statistical traffic data, and measured travel time data in the driving tests in northern Ibaraki Prefecture was regarded as the actual ones. From a total performance point of view, traffic data for the evaluation included various traffic conditions from smooth to heavy congestion. What should be compared with the travel time data estimated by each method is the travel time estimated from static travel speed in conventional navigation systems. As shown in Figures 9 to 11, all the estimation methods which we proposed could improve the accuracy of travel times through comparison with

conventional navigation systems, and they were certainly effective for improving the accuracy and the amount of traffic data.

	Average error ratio
Conventional travel time	25.5%
Statistical travel time	18.9%

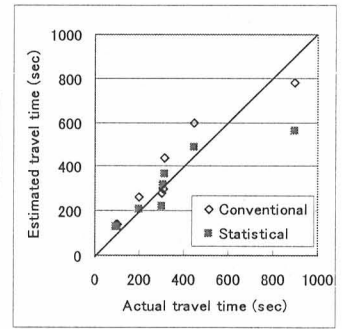


Figure 9. Comparison between the travel time accuracy of Estimation-1 and conventional navigation

	Average error ratio
Conventional travel time	29.0%
Statistical travel time	16.9%

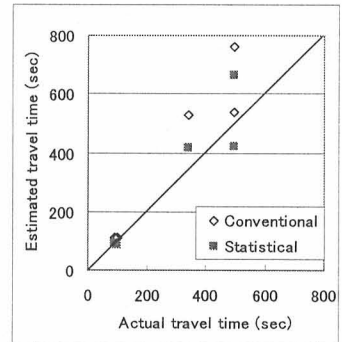


Figure 10. Comparison between the travel time accuracy of Estimation-2 and conventional navigation

	Average error ratio
Conventional travel time	43.5%
Statistical travel time	20.4%

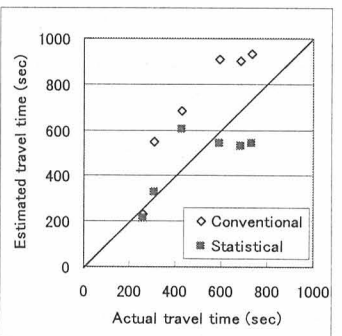


Figure 11. Comparison between the travel time accuracy of Estimation-3 and conventional navigation

4. Conclusions

This paper proposed estimation methods for statistical traffic data which navigation systems use for route search and evaluated the performance of each through driving tests. The following findings were provided.

- (1) It was clear that travel time information currently has some problems in the accuracy and the amount of data used for route search in navigation systems.
- (2) Classification of statistical traffic data was studied in order to make the data accurate. As a result, four classifications, which might be practical and accurate enough to use in navigation systems, were analyzed.
- (3) Methods for filtering unusual traffic data statistically were proposed in order to make the data stable and accurate. Evaluating the accuracy of the statistical traffic data, its performance was by no means inferior to that of VICS information in real time.
- (4) Three estimation methods were proposed for the purpose of increasing the amount of travel time information without spoiling its accuracy. From the evaluation, we found each method could increase the amount and improve the accuracy of travel time considerably more than conventional methods.

As described above, efficient use of the current VICS information enables an improvement in the amount and accuracy of traffic data, and certainly each estimation method performed well. Also, when a navigation system uses the statistical traffic data, the appropriateness of the searched route and the accuracy of predicted arrival time at destination might be improved over conventional navigation systems. Their effects may raise the utility of navigation systems.

5. References

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