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Cross comparison of spatial partitioning methods for urban transportation network

Shin Hirabayashi[a], Takao Dantsuji[a], Qian Ge[a] and Daisuke Fukuda[a]

[a]*Department of Civil and Environmental Engineering, School of Environment and Society, Tokyo Institute of Technology,*

Abstract

Although macroscopic traffic flow theory has been developed these days, partitioning method based for well-defined macroscopic fundamental diagram (MFD) has not been well explored yet. Thus, we compare two specific partitioning methods proposed by Ji and Geroliminis (2012) and Ge et al. (2016), respectively. With the former method the number of partitions is arbitrary, but the latter method can determine the number of partition automatically. Actual traffic data from detectors distributed in the central business district of Tokyo has been used for empirical comparison. It is found that the results of these two partitioning methods are similar in terms of the number of partitions and the shapes of neighbors. For the well-definedness of the estimated MFDs for each community, the approach by Ji and Geroliminis outperformed Ge et al. but the differences are small.

Keywords: Macroscopic funtamental diagra, partitoning, community detection;

1. Introduction

In central business district areas with huge vehicular traffic flow, serious traffic congestion happens. It leads to waste of fuel and time due to low speed, and so on. To mitigate congestion, traffic management schemes such as road pricing and perimeter traffic restraint control should be considered to be implemented. Recent developments in macroscopic traffic flow theory, particularly the concept of macroscopic fundamental diagram (MFD) would be useful for the network-level traffic management. The MFD describes the network-level relationship between the trip production and the vehicle accumulation in a spatial aggregate of the area as theoretically analyzed by Daganzo (2007). The existence of MFD has been empirically confirmed by Geroliminis and Daganzo (2008) using actual data in the area of Yokohama downtown. Literature has shown that the MFD is a sensitive of the network infrastructure and

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control strategy, but not necessarily of the traffic demand. This argument would be important for the network-level management. Moreover, the MFD is well-defined if a subnetwork of interest is homogenous with similar links, which would be prerequisite to implement the management schemes properly. In the existing MFDs, however, there might exist high scatters of observed points and hysteresis loop (Buisson and Ladier, 2009; Wang et al., 2017) because of the heterogeneity of the networks with different level of congestion. One possible solution for these issues is partitioning a heterogeneous network into some homogeneous subnetworks.

There are some studies on partitioning into homogenous networks. The seminal work by Ji and Geroliminis (2012) proposed the clustering method of the heterogeneous networks based on the spatial conditions of congestion (in terms of traffic density) at a specific time period. Their method consists of three steps: (1) segments area into communities which consist of similarly dense links; (2) merges similarly dense communities until communities reach the proper number; and (3) adjusts boundaries between communities to minimize the scattering of traffic state. The advantage of Ji and Geroliminis method is that it proposes the index of compactness of communities. But it is implemented only in static state and it needed to be extended to dynamic partitioning cases. On the other hand, Ge et al. (2016) proposed the partitioning method based on the concept of network (or graph metric), namely modularity. This method consists of two steps: (1) calculating link weights considering free flow speed and capacity of the link; (2) it calculates modularity with link weights calculated in first step and partitions an area. Advantages of this method would be its efficiency of calculation and automatic adjustment to the size of appropriate subnetwork. The method by Ge et al. would be suitable for large scale network due to its efficiency but it has a limitation that MFDs in each subnetwork still exhibit high scattering because it only uses the information of free flow state.

Obviously, different area partitioning methods would provide different outputs (i.e. subnetworks). Even if the same method is applied to same heterogeneous network, the shapes of subnetworks might be different due to the variance of speed and density at different time periods. Furthermore, most of existing studies on partitioning only utilize synthetic traffic data generated from traffic simulations. It is thus quite important to investigate the applicability of different partitioning strategies using real data. Although some studies on spatial partitioning method for urban transportation networks exists, to the knowledge of authors, there would be no studies on cross comparison of these methods using real data. In this study, we compare existing spatial partitioning methods proposed by Ji and Geroliminis (2012) and Ge et al. (2016) using real traffic data collected in the arterial network.

2. Methodology

2.1 Ji & Geroliminis (2012) approach

We shall start to show the partitioning method proposed by Ji and Geroliminis (2012). There are three aims of this approach as mentioned in the previous section. To this end, they developed a graph-based algorithm for transportation system, namely Normalized Cut Algorithm (NCut) proposed by Shi and Malik (2000). In the model, the links in a road network are modeled as nodes in undirected graph G and the links are weighted by a density value d_i at a certain time. Then, weighted distance $w(i,j)$ between link i and link j is defined as

$$w(i,j) = \begin{cases} \exp\left(-\left(d_i - d_j\right)^2\right) & \text{if } r(i,j) = 1 \\ 0 & \text{otherwise} \end{cases}$$

where $r(i,j)$ is the length of the shortest path between link i and link j, that is $r(i,j) = 1$ if link i and link j are adjacent. Then, consider to partition a graph $G = (V, E)$ where V is a set of nodes and E is a set of edges in G into two networks. By defining the similarity between two networks (network A and network B) as $\text{cut}(A,B) = \sum_{u\epsilon A, v\epsilon B} w(u,v)$, the total dissimilarity, $\text{Ncut}(A,B)$ between two partitioned network and the total similarity within each partitioned network is estimated as follows.

$$\text{Ncut}(A,B) = \frac{cut(A,B)}{cut(A,V)} + \frac{cut(A,B)}{cut(A,V)}$$

$$\text{Nassoc}(A,B) = \frac{cut(A,A)}{cut(A,V)} + \frac{cut(B,B)}{cut(B,V)}$$

As it is straightforward that $\text{Ncut}(A,B) = 2 - \text{Nassoc}(A,B)$, minimizing $\text{Ncut}(A,B)$ is equivalent to maximizing $\text{Nassoc}(A,B)$. Although minimizing $\text{Ncut}(A,B)$ exactly is NP-complete, Shi and Malik (2000) showed that the discrete solution can be approximated by solving an eigenvalue system in the real value domain. Thus, by solving the equivalent eigenvalue system, the eigenvector with the second smallest eigenvalue is obtained. That is utilized to bipartition the graph. Then, apply it to the partitioned cluster repeatedly until more clusters than desired are created.

This process is the first step.

Afterwards, the second step is to merge two clusters in which means of link densities are closest among all clusters to estimate the optimal number of clusters.

As the third step, boundary adjustment is implemented to reduce the variance of link densities. The idea is that suppose link k is on the boundary between cluster A and B and assume $k \in B$ which is the set of links in cluster B, if the following criterions are satisfied, link k is moved to cluster A since this makes both density variances of clusters decreased.

$$\begin{cases} \dfrac{(d_i - u_A)^2}{Var(A)} < \dfrac{N_A + 1}{N_A} \\ \dfrac{(d_i - u_{B\setminus k})^2}{Var(B \setminus k)} < \dfrac{N_B}{N_B - 1} \end{cases}$$

where $Var(\cdot),\ u, N$ are the variance and mean of the link densities and the number of links in cluster, respectively. Note that $B \setminus k$ is defined as the set of all links in cluster B except link k. They develop this idea further to prevent the spatial shapes from not being compact. Namely, they apply it not to an independent link but to spatially consecutive links on the boundaries as follows.

$$\begin{cases} \dfrac{(u_A - u_Y)^2}{Var(A) - Var(Y)} < \dfrac{N_A + N_Y}{N_A} \\ \dfrac{(u_{B\setminus k} - u_Y)^2}{Var(B \setminus k) - Var(Y)} < \dfrac{N_{B\setminus Y}}{N_B - 1} \end{cases}$$

where Y is a group of consecutive links from cluster B to A. Thus, the algorithm of the boundary adjustment is done as the following steps; (1) find all links on the boundary and a spatial sequence related to the links is identified. (2) find a subgroup of consecutive links that satisfy the equation above if exists, the algorithm stops otherwise. (3) find the subgroup that minimizes the total variance the most, and move it to the cluster B and update the partitioning. (4) go to step (1).

To evaluate the different partitioned network and find the optimal number of clusters, the three metrics are utilized. The first metric to evaluate the partitioning is “NcutSilhouette” (NS) defined as

$$NS_k = \frac{\sum_{A\in C} NS_k(A)}{k}$$

where $NS_k(A) = \frac{2Var(A)}{\{Var(A)+Var(B)+(u_A-u_B)^2\}}$, C is the set of clusters and k is the total number of clusters. Note that cluster B is the cluster which is the most similar with cluster A among the cluster A’s neighbours. Moreover, the total variance of the clusters is used as the second metrics to evaluate the quality of the partitioning by the following equation.

$$TV = \sum\nolimits_{A\in C} N_A\, Var(A)$$

the homogeneity of the links densities can be estimated by NS_k and TV.

The third metrics is the shape metrics. Define that a clockwise sequence for the nodes on the boundary is “...,(i-1), i, (i+1), ...”. Then, the degree of the smoothness can be estimated by

$$\text{BoundaryAngle}(i) = \angle(i-1)i(i+1)$$

Note that the angle is less than π at node i. then, it can be said that if a boundary angle is more than a predefined threshold (e.g. $\pi/2$), it is smooth. For non-smooth nodes, the area of a triangle by node (i-1), i and (i+1) is calculated to estimate the non-smoothness of the region R as the follows

$$\text{NonSmoothness}(R) = \sum_i A(i)/A(R)$$

where $A(i)$ is the area of a non-smooth boundary node and $A(R)$ is the area of a region R.

2.2 Ge et al. (2016) approach

In this approach, *modularity* proposed by Newman and Girvan (2004) is used to evaluate the goodness of subnetworks, which is defined as

$$Q = \frac{1}{2m}\sum_{ij}(A_{ij} - P_{ij})\delta(C_i, C_j)$$

where m is the sum of link weights in a network, A_{ij} is the adjacent matrix of links, P_{ij} is the expected number of links between i and j in a randomized network and $\delta(C_i, C_j)$ is 1 if links i and j are belong to the same community and 0 otherwise. Note that weight of a link for transportation network is discussed later. In the Louvain modularity (Blondel et al., 2008), $P_{ij} = k_i k_j / 2m$ where k_i and k_j is the total link weight for node i and j, respectively.

As the optimization problem that maximizes Q is NP-hard, the following approximation method is widely used (i.e. The Louvain method)

1. Initialize the network and each node belongs an individual community.
2. Reassign each node's community to its new neighbour to maximum Q.
3. Coarse the network by viewing the new communities as larger node. By summing all internal links in a community, the weight is updated.
4. Repeat until convergence.

Regarding the generalized link weight, only data on supply side such as the link length is utilized in Ge et al. approach since the partitioning is an ad hoc basis if the data on the demand side, that is temporal data determined by traffic condition at a certain time, is used. That is one of the main differences between Ji and Geroliminis approach and Ge et al. approach.

Therefore, the generalized link weight is defined as

$$u_{ij} = d_{ij} + w_1 v_{ij}^f + w_2 f_{ij}^c$$

where d_{ij} is the link ij length, v_{ij}^f is the free-flow speed on link ij, f_{ij}^c is the capacity of link ij. As speed and capacity varies quite a lot depending on the link property, they cast both v_{ij}^f and f_{ij}^c to the interval [0,1] as follows:

$$v_m = \max\{\dots v_{ij}^f \dots\},\ f_m = \max\{\dots f_{ij}^c \dots\},\ \text{and}\ u_{ij} = d_{ij} + w\left(\frac{v_{ij}^f}{v_m} + \frac{f_{ij}^c}{f_m}\right).$$

3. Comparison

3.1 Data

The targeted area in this study is the Tokyo CBD where Imperial Palace, Tokyo station and the central district of national government are included (Fig.3.1). The area is approximately 40 km^2. Streets have 1-6 lanes in each direction. The network consists of 409 links and 260 nodes for arterials. Traffic data from 2,158 detectors can be used for the analysis. These fixed detectors are mainly ultrasonic, optical or pictorial based and located every 60-100 meters along arterials. Vehicle count data and time-occupancy data every 2.5 minutes for one month (July 2017) are available. Note that since there are links where the fixed detectors are not installed, we estimate traffic conditions of these links by averaging the traffic condition of surrounding links. If it is possible to combined detectors data with another type of data such as taxi probe data, we can estimate those traffic condition more precisely. Moreover, there are actually some studies on missing data imputation (Eom et al., 2006, Bae et al., 2018), thus utilizing these methods is also one of the solutions to predict conditions more precisely. That shall be reported in the future research paper. Fig. 3.2 illustrates the estimated MFD from all data of the detectors. The maximum flow is approximately 550 veh./hour when the occupancy is 12.5 %. The

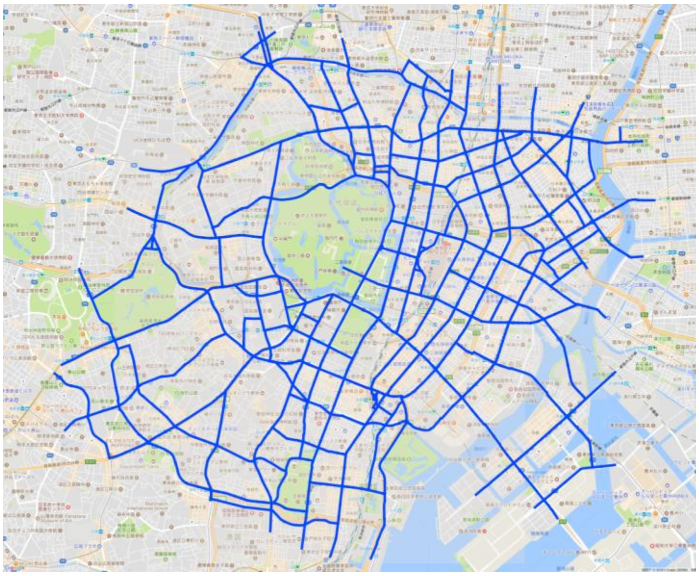

Fig. 3.1 Target area and arterial network

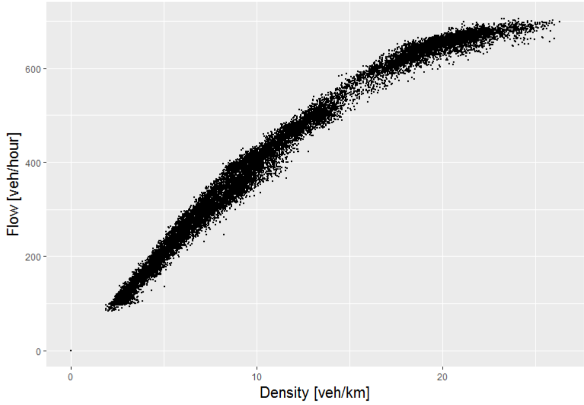

Fig.3.2 Estimated MFD for the whole area

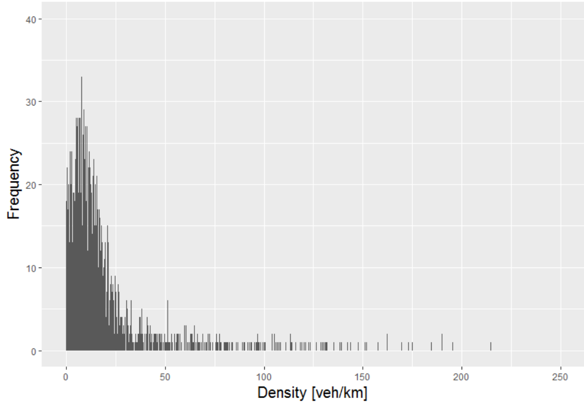

Fig.3.3 Histogram of link density

downslope curve cannot be observed from this area. One of the possible reason for this is that some parts are congested on the other hands the others are uncongested. This can be observed in Fig. 3.3 of the histogram of occupancy at a specific time (9:15 on 5th). Obviously, congestion is not evenly distributed and the distribution is heavily skewed to the right.

3.2. Implementation of Two Approaches

When comparing the methods, Ji and Geroliminis (2012) is the data from the demand side. We use the occupancy data at 9:15 on 5th which is one of the semi-congested state. On the other hand, Ge et al. (2016) is the data from the supply side, thus we use the capacity data. However, it was difficult to obtain the data, we calculate it from maximum flow observed by detectors in July 2017.

3.3. Comparison Results

First, we implemented Ge et al. approach to Tokyo CBD area, changing weight of capacity 0.01 to 50.0. The results are shown in Table 3.1. When weight is 0.01, not only the Modularity score is optimal, but also average NS is optimal in these five. And as you can see, the proper number of partition may be around 12, we implemented Ji and Geroliminis approach until taking over 12 communities. The results are shown in Table 3.2. After reaching 15 communities, we merged similar communities. But the average NS does not monotonically decrease. On the other hand, average NS became minimum when the number of communities is 12. From this, we guess both Ge et al. approach and Ji and Geroliminis have optimal solution around 12 communities.

From the scatter plot of traffic state (Figs. 3.4, 3.5), it is obvious that there are high scatters in some communities. On the other hand, in several communities MFD are well-defined.

When we draw above best partitioning on GIS application, we can get below images (Fig. 3.6 and Fig. 3.7). We can state that the partitioning border are similar each other. For example, around Tokyo station which is located right side of central white hall (Imperial Palace), there are three communities which are in north side, south side, and east side.

Table 3.1 NS metric, Modularity score and the number of communities by Ge et al. approach

Weight	0.01	1.0	1.2	9.0	50.0
# of communities	16	13	13	11	11
Modularity score	**0.8151**	0.7338	0.7849	0.7820	0.7845
Average NS	**0.9252**	1.0315	1.0210	1.0290	0.9527

Table 3.2 Average NS by Ji and Geroliminis approach

# of communities	2	3	4	5	6	7	8	9	10	11
Average NS	0.9762	1.0182	0.9985	1.0219	0.9936	1.0329	0.9403	0.9180	0.8736	0.8888
# of communities	12	13	14	15	14	13	12	11		
Average NS	**0.8599**	0.9087	0.8985	0.9778	0.9501	0.9568	0.9466	0.9637		

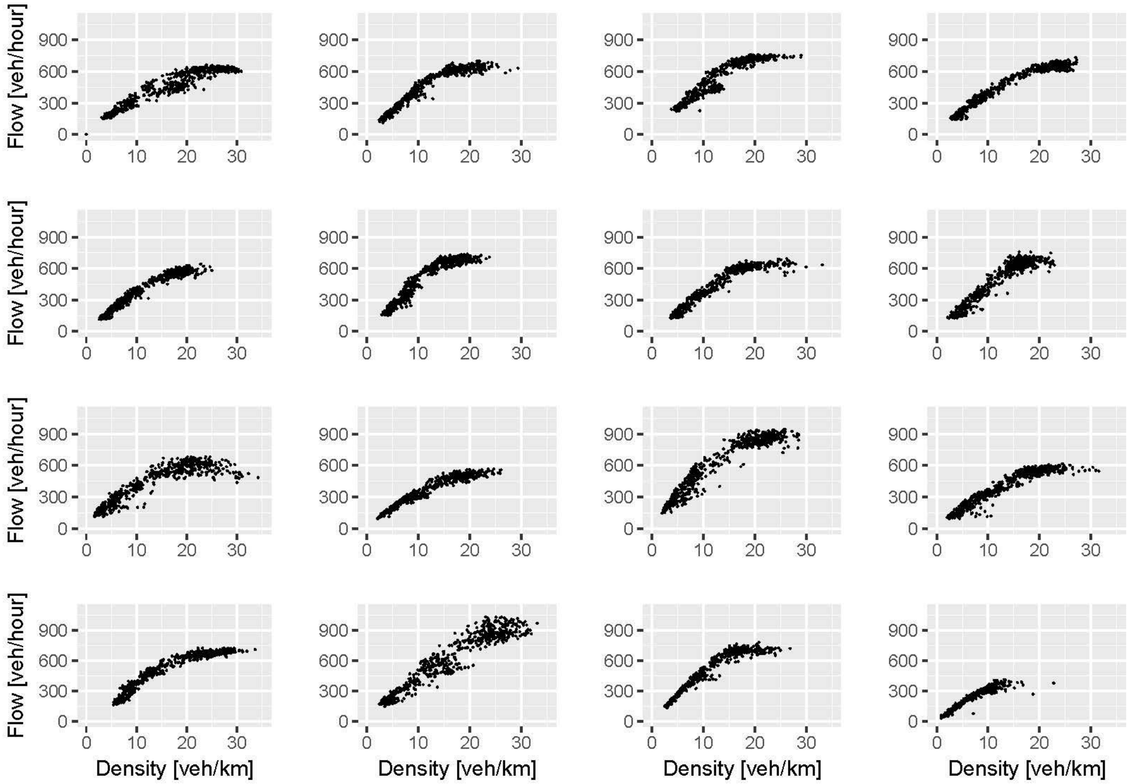

Fig. 3.4 Scatter plot by Ge et al. approach (from upper left to bottom right, community ID=1,2,3,…)

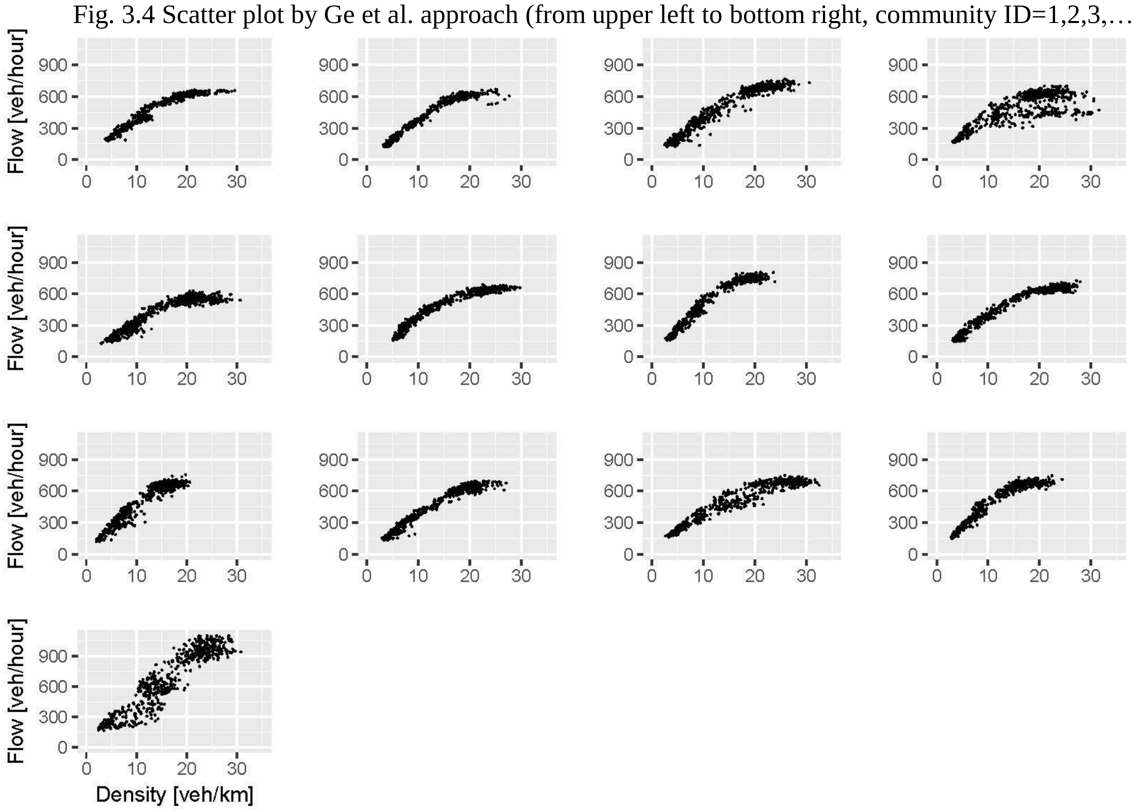

Fig. 3.5 Scatter plot by Ge et al. approach (from upper left to bottom right, community ID=1,2,3,…)

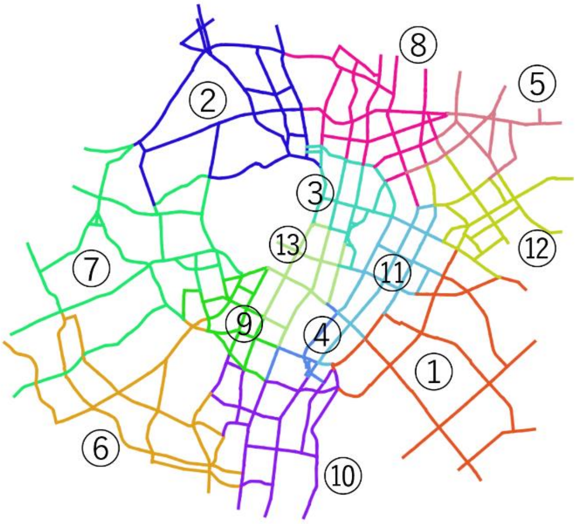

Fig. 3.6 Partitioning result by Ji and Geroliminis approach

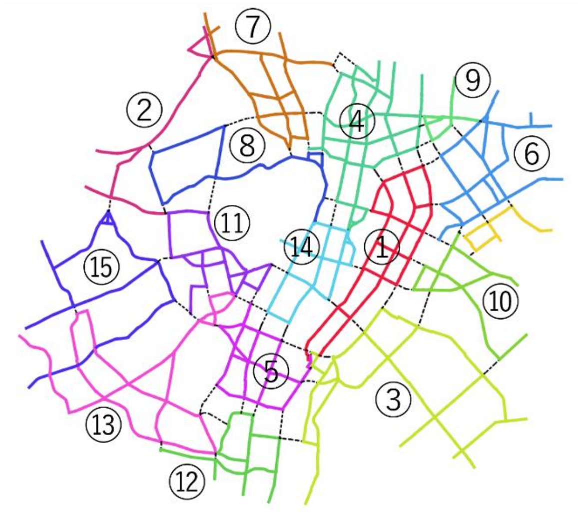

Fig. 3.7 Partitioning result by Ge et al. approach

Then we measured how these plots are scattering with fitted curve. We regressed density with respect to flow by specifying a cubic function (with three parameters except constant term) for each neighborhood using the plotted data shonw in Figs. 3.5 and 3.6. For the sake of space, only adjusted determination coefficients of the measurement are shown in Table 3.3. In Ge et al. approach, all of adjusted R^2 are greater than 0.9, while some of that of Ji and Geroliminis approach are below 0.9. And average of former part is 0.01 higher than counterpart. Hence we can state that former approach shows lower scattering.

Table 3.3 adjusted determination coefficient of Ge et al. approach

Community ID	1	2	3	4	5	6	7	8	9	10
Adjusted R^2	0.927	0.970	0.926	0.979	0.975	0.958	0.966	0.955	0.924	0.967

Community ID	11	12	13	14	15	16	Average
Adjusted R^2	0.949	0.946	0.956	0.925	0.973	0.968	0.954

Table 3.4 adjusted determination coefficient of Ji and Geroliminis approach

Community ID	1	2	3	4	5	6	7	8	9	10
Adjusted R^2	0.968	0.985	0.964	0.746	0.945	0.971	0.980	0.982	0.954	0.976

Community ID	11	12	13	Average
Adjusted R^2	0.941	0.975	0.881	0.944

4. Discussions

When implementing Ge et al. approach, some communities became relatively small. On the other hand, because we can implement arbitrary partitioning, size of community is homogeneous. If we will utilize former method, it is needed to develop the size problem. One of the solutions may be to adopt new variables, for example, free flow speed, pavement state, safety, and so on. Because current approach is lack of a variety of explanatory variables, weights of links in modularity method are inaccurately calculated.

Ji and Geroliminis approach divides links, but Ge et al. approach divides nodes, so latter method leads some stray links. When we implement road pricing or perimeter traffic restraint control, such links may annoy traffic manager. This method may be good at inter city transportation, hence we should develop such disadvantages.

These two methods partition Tokyo CBD similarly, but there exist some scatterings in plot of traffic state. In detail, both methods show optimal partitioning around 12 communities, and several partitioning boundaries are the same.

When comparing the methods, Ji and Geroliminis utilizes the data from the demand side. More specifically, we use the occupancy at 9:15 on 5th which is one of the semi-congested state. On the other hand, Ge et al. uses the data from the supply side. It is so difficult to obtain free flow speed data that we use only link length and capacity data. Alternatively, the capacity data is estimated from maximum flow in each link observed by detectors in July 2017 and utilized. In the former method, there are (2) merging procedure and (3) adjusting procedure, but the latter method does not contain these steps. Hence we compare (1) step of former method and latter one.

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References

Bae, B., Kim, H., Lim, H., Liu, Y., Han, L.D. and Freeze, P.B., 2018. Missing data imputation for traffic flow speed using spatio-temporal cokriging. Transportation Research Part C: Emerging Technologies, 88, pp.124-139.

Buisson, C. and Ladier, C., 2009. Exploring the impact of homogeneity of traffic measurements on the existence of macroscopic fundamental diagrams. Transportation Research Record: Journal of the Transportation Research Board, (2124), pp.127-136.

Daganzo, C.F., 2007. Urban gridlock: Macroscopic modeling and mitigation approaches. Transportation Research Part B: Methodological, 41(1), pp.49-62.

Eom, J., Park, M., Heo, T.Y. and Huntsinger, L., 2006. Improving the prediction of annual average daily traffic for nonfreeway facilities by applying a spatial statistical method. Transportation Research Record: Journal of the Transportation Research Board, (1968), pp.20-29.

Ge, Q., Wang, P., & Fukuda, D., 2016. A Community Detection for Identifying Neighborhoods. Proceedings of the 21st HKSTS (Hong Kong Society for Transportation Studies) Conference.

Geroliminis, N. and Daganzo, C.F., 2008. Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. Transportation Research Part B: Methodological, 42(9), pp.759-770.

Ji, Y. and Geroliminis, N., 2012. On the spatial partitioning of urban transportation networks. Transportation Research Part B: Methodological, 46(10), pp.1639-1656.

Wang, P., Wada, K. and Akamatsu, T., 2017. An empirical analysis on macroscopic fundamental diagram for urban street networks based on long-term detectors data: Characteristics and its mechanism. Transportation Research Board 96th Annual Meeting, No. 17-03715.