SPATIAL AND TEMPORAL COMMUNITY DETECTION OF CAR MOBILITY NETWORK IN METRO MANILA

B. G. Carcellar, III [1,2]*, A. C. Blanco[1], M. Nagai[2]

[1] Department of Geodetic Engineering, College of Engineering, University of the Philippines, Diliman
(bgcarcellar, acblanco) @up.edu.ph
[2] Department of Construction and Environmental Engineering, Graduate School of Science and Technology for Innovation, Yamaguchi University – (b014ve, nagaim) @yamaguchi-u.ac.jp

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ABSTRACT:

Transportation Network Companies (TNCs) like Uber utilize GPS and wireless connection for passenger pickup, driver navigation, and passenger drop off. Location-based information from Uber in aggregated form has been made publicly available. They capture instantaneous traffic situation of an area, which makes describing spatiotemporal traffic characteristics of the area possible. Such information is valuable, especially in highly urbanized areas like Manila that experience heavy traffic. In this research, a methodology for identifying the underlying city structure and traffic patterns in Metro Manila was developed from the Uber trip information. The trip information was modelled as a complex network and Infomap community detection was utilized to group areas with ease of access. From Uber trip dataset, the data was segregated into different hours-of-day and for each hour-of-day, a directed-weighted temporal network was generated. Hours-of-day with similar traffic characteristics were also grouped together to form hour groups. From the results of the network characterization, hours-of-day were grouped into six hour groups; 00 to 04 hours-of-day in hour group 1, 05 to 07 hours-of-day in group 2, 08 to 12 hours-of-day in group 3, 13 to 15 in group 4, 16 to 19 in group 5, and 20 to 23 in group 6. Major roads as well as river networks were observed to be the major skeleton and boundaries of the generated clusters

1. INTRODUCTION

1.1 Background

Highly urbanized cities in the Philippines, like those in Metro Manila, experience extreme traffic congestion problems. Metro Manila drivers were identified by Waze as the least satisfied motorists among the 39 countries surveyed. In its third annual global Driver Satisfaction Index, the Philippines obtained a satisfaction index of 3.02 over a score of 10, citing "unhappiness with traffic jam length, commute time and helpfulness of the driving community," as the main reasons for the low score (“Waze: PH the worst place to drive,” 2017). Also, a study by Japan International Cooperation Agency (JICA) revealed that the current traffic condition in the Philippines costs around Php 6 billion a day. The study further quantified the effects of traffic in Metro Manila as households are expected to spend 20% of their monthly income in transport alone. This will increase the traffic demand by 13% by the year 2030, if no intervention is done by the government (“JICA transport study lists strategies for congestion-free MM by 2030,” 2014).

With the increase in demand of public transport, companies develop business models to aid in addressing the needs of the growing number of commuters. One such company is Uber, classified as a Transportation Network Company (TNC) initially pitched by Travis Kalanick and Garrett Camp in 2008 (“The Uber story,” 2016). The concept of Uber and mostly other Transportation Network Companies is to have an easier networking of passengers and drivers by utilizing wireless connection and Global Positioning System (GPS). For a decade, Uber expanded to cater other countries, amidst legal complaints from government and taxi franchise alike (Nistal and Regidor, 2016). Last February 2014, Uber was formally launched in Metro Manila and nearby areas (Ma, 2014). Since its introduction in the Philippine transportation market, Uber has generated enough users and drivers to continue its franchise until April 2018. According to Nistal & Regidor (2016), Uber was identified as a better alternative to taxicabs because of its “edge in safety through effective information dissemination, convenience through technological advancements in booking and GPS, and comfort through newer cars and performance conscious drivers”.

Since TNCs rely on wireless and positioning technologies, information such as trip durations, routes, start trip time, and end trip time were stored to better manage their booking and pricing algorithms. Companies record the initial location of the rider, the route the driver took to reach the destination, and the total driving time among other information. These information captures the instantaneous traffic situation of an area, which in turn provides a good sample of the cars travelling along the traffic. Large amount of spatiotemporal traffic information such as these are valuable for better road infrastructure planning and traffic assessment of the area.

With the ongoing traffic congestion problems in Metro Manila, it is good to fully understand the traffic situation in the area. With better understanding, management strategies and policies can be formulated to address properly the traffic problem.

1.2 Objectives and Significance

This research aims to do a spatiotemporal characterization of the traffic situation of the area using the traffic reflected in Uber Movement dataset. The characterization done aims to better understand the changes of traffic in Metro Manila in a single day and find which areas are more connected.

Specifically, the research aims to develop a method that can extract the underlying city structure from the Uber Movement dataset which can be useful for analysis of similar form of dataset. This traffic information is then analyzed and characterized to identify areas where cars have similar travel patterns for short, medium, and long travel times. Aside from spatial grouping, hourly grouping is also done to determine which hours of the day are very much similar in traffic situation.

1.3 Scope and Limitations

In this study, only a certain part of Metro Manila is covered by the Uber Movement dataset. As shown in Figure 1, only the central part of Metro Manila is included and observed in this research. Although the dataset cover most of the Metro Manila area, cities such as Quezon City, Parañaque, and Marikina are not covered fully by the dataset.

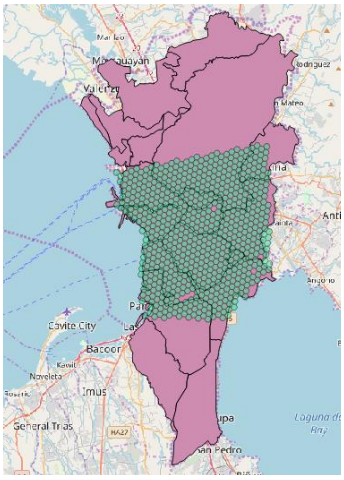

Figure 1. Uber Movement coverage (cyan hexagon) overlaid with Metro Manila shapefile

The dataset used in this research are aggregated in quarters of year. Also, since April 9, 2018, Uber has ceased its operations in the Philippines. With this, the Uber trip dataset available through the Uber Movement are limited only from the first quarter of 2016 to the second quarter of 2017. As of this moment, the Uber trip data for Manila has also been removed from the Uber Movement website, making it unavailable to the public.

The concept of the study relies on the Uber Movement dataset as a sample dataset for the cars in Metro Manila. In this case, utilizing only the Uber Movement will only reflect a certain behavior of traffic since this provides a certain sample of drivers only. Particularly, the reflected behavior in Uber drivers will mostly be on the reliance on third party applications for navigation, since most Uber drivers use these for quicker travel. And so, the movement of these cars provide a good understanding on the traffic situation of the quickest routes during that time. The source and the destination of the trips depend on the demand of the Uber user during that time. In this case, a certain target market is only reflected by using Uber Movement data, for which it will be harder to generalize the travel demand basing only from this data. Other mobility types such as private cars, taxis, buses, UVs, jeepneys, and tricycles can be used in order to get a full understanding on the travel demand. In this study, the focus will be on the traffic, relating it to the travel speeds and travel time, and how connectivity evolves in space and time.

Since Uber caters to a specific market, the findings of this research do not necessarily reflect the general human mobility patterns and captures only the car mobility. Human mobility requires social aspect in the analysis aside from the technical data on speeds, such as the Uber data. Furthermore, the results of this study can be used as an input in studying human mobility patterns, serving as the information on road or zone speeds, since car mobility patterns is just one of the important aspects in looking at the bigger picture which is human mobility. Other data sources such as transportation routes, actual demand, and demographic background are needed in order to fully capture human mobility.

Also, one limitation of this research is the form of the Uber data wherein the only traffic information is the aggregated travel time. No information about the actual path of the car is provided for security reasons. However, the car path dataset could significantly increase the spatial aspect of characterization. Compared to the study wherein the nodes are spaced around 700 meters apart, a car path dataset can even densify the nodes into street segment level and have a much in-depth spatial characterization. Taxi GPS data which contain actual travelling path is really a good starting point in trying to have a better picture of car mobility in a smaller spatial scale. Another information that is not available to the Uber data is the actual number of Uber trips for each aggregated data. In this case, there is no way of knowing the volume of the traffic. Although this was compensated by associating travel speeds, the actual volume is still a helpful data to use in this case.

2. REVIEW OF LITERATURE

2.1 Networks for Traffic Identification

Taxi trip data has been one of the earliest sources information for city structure investigation. Early studies date back to 1970s wherein taxi trip information are utilized to determine the pattern flows of taxis as well as the location of the trip origin and destinations (Goddard, 1970). In the recent years, studies have been made that utilized taxi trip data as a spatio-temporal information to extract accessibility of zones in the study area (M. Gao et al., 2013; Li et al., 2011). Contributing to this is the usage of information from location-aware mobile devices which are also utilized in some studies focused on the transportation analysis (S. Gao et al., 2013; Fang et al., 2012).

Nowadays, a shift in the form of traffic data is seen from the traditional travel surveys to online footprints from mobile devices with the help of navigation services, in which these data provide more accurate and reliable form of travel information (Lu and Liu, 2012). Majority of recent researches dealing with such data utilized complex networks to model car movement (Redelosa and Lim, 2018; Liu et al., 2015; Pearson et al., 2018).

Community detection algorithms have been widely used to understand these hidden urban structures by dividing a network into sub-networks that are strongly connected within themselves (Liu et al., 2015). Some researches aimed to identify if the established administrative boundaries properly reflect the boundaries that are created through examining the interaction data of people (Ratti et al., 2010; Thiemann et al., 2010). For taxi networks, the clustering algorithm preferred is the Infomap. The Infomap algorthim optimizes the map equation in order to generate the clusters of nodes that are densely connected (Rosvall and Bergstrom, 2008). Infomap is preferred since this algorithm can handle weighted and directed networks as well as provide a quick and stable calculation (Fortunato, 2010).

2.2 Studies utilizing Uber Movement

Aside from taxi and bus data, another source of traffic dataset is the Uber Movement which opened its aggregated and anonymized travel dataset to the public for some selected areas (Gilbertson, 2017), as what is used in this research. It has been proven through recent study that Uber has indeed decreased the traffic congestion particularly in urban areas (Lu and Liu, 2012; Li et al., 2016).

Since Uber Movement data is aggregated, the actual path of the car is not available in public for privacy purposes (“Uber Movement: Travel times calculation methodolog,” 2018). Only the source ID, the destination ID, and the travel time statistics are part of the dataset. The varying travel time in Uber Movement dataset makes it beneficial for tracking traffic other than the usual available information such as Google Maps and Waze. The travel times in Uber Movement are in fact much shorter compared to Google Maps prediction (Wu, 2019). This may be because Uber drivers tend to have guidance from third party routing apps such as Waze for navigation, compared to the general population which rely on their stored knowledge of the routes. Aside from this, there is an additional incentive for Uber drivers to complete the trips in a shorter travel period which makes the uber movement data an estimator of travel time for experienced drivers (Wu, 2019).

Aside from this comparison, a study has also been made using Uber Movement dataset for modelling of travel speeds using machine learning (Uzel, 2018). Estimating the speeds need to have a good estimate of the distance travelled by the car which is of course not available through the Uber Movement dataset. In this case, the use of routing service APIs available online can provide a better estimate for the distance the car has travelled. Google Maps Routes service is often used for this purpose (Wang and Xu, 2011; Li and Yiu, 2015) although using this can be costly. Other open source routing services such as Open Source Routing Machine (OSRM) and Open Route Service (ORS) can provide same distance and routing techniques from Google Maps Routes API provide, for free (Uzel, 2018). Usually, these open source routing services provide these computations through request with a daily quota per key. In this study, distances are calculated using the Open Route Service Time-Distance Matrix API service through python binding in order to better estimate the total distance travelled by the car from its source to the destination.

3. METHODOLOGY

The main idea of the study lies on the concept of understanding Metro Manila mobility issues by observing mobility patterns and characteristics. Towards this goal, the aim is to extract spatial and temporal mobility patterns from Metro Manila Uber Movement data. This conceptual framework is illustrated in Figure 2 below.

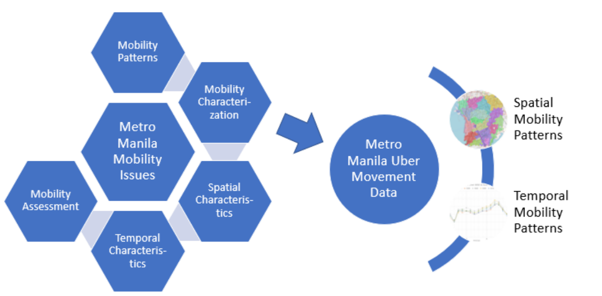

Figure 2. Conceptual framework for characterizing spatial and temporal mobility patterns

The presence of mobility patterns is the main assumption of the research; the main goal of which is to determine these mobility patterns. Characterizing these mobility patters can be done using various available datasets but for this research, the dataset used is the Metro Manila Uber Movement data. The characteristics obtained have implications about the mobility within the area, as will be explained in the succeeding sections. The mobility characteristics that were extracted in this research were classified into two major characterization types: the spatial and the temporal characteristics. The underlying city structure and travel patterns were identified by extracting areas that are well connected, i.e., there is an ease in movement within these areas. Identifying such areas may aid in understanding effectiveness of the barangay-based traffic-analysis zones that is currently being used for traffic management (Abuzo et al., 2017).

For the temporal characteristics, the changes in travel patterns and location of important areas across different hours of the day were examined. Grouping of well-connected areas were observed at different hours-of-day. The changes in the grouping provide dynamic characterization, i.e., which areas are well connected during rush hours, daytime, night time, etc.

Translating the conceptual framework into specific processes is done by forming the research workflow. This is represented by the methodological framework as shown in Figure 3.

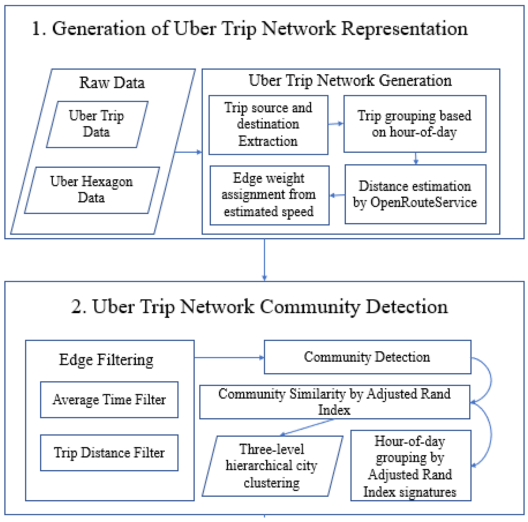

Figure 3. Methodological framework trip network representation and community detection

The workflow of the research is divided into two (2) major steps namely, 1) Uber Trip Network Generation; and 2) Network Community Detection. The first part discusses the pertinent techniques used in transforming the Uber Movement to a complex network, and the succeeding method was used to extract characteristics of the car mobility by community detection.

3.1 Generation of Uber Trip Network

The main source of information for this research is the Uber Movement Manila Travel Time dataset. The raw travel time dataset was used, as well as the corresponding hexagonal GeoJSON data of Manila, to create a geodatabase. The generated geodatabase was used to extract relevant information for the succeeding characterization processes.

The Uber Movement dataset is anonymized and aggregated. The form of Uber Movement dataset used in this research are hourly aggregates for the four quarters in 2016, and the first two quarters in 2017. Particularly, the information utilized in this research are the mean travel time from one location to another for each of the 24 hours in a day.

The Metro Manila GeoJSON dataset provides location information for the trips in form of zone IDs of the source and destination in Manila Uber dataset. Linking the locational information to the temporal information in Uber Movement data, both spatial and temporal characterization can be done. Figure 4 shows the coverage of the hexagons for the area.

Figure 4. Metro Manila hexagons from Uber Movement

The average speed of the trip is estimated using the distance from Open Routing Service and the mean trip duration from Uber. The trips were segregated based on the hour of the day it is recorded. Each trip corresponds to an edge of the network, and the nodes of the edges are the zones and destinations, and the speeds as the weights of the edges, thereby creating 24 weighted and directed graphs, one for each hour of the day.

3.2 Uber Trip Network Community Detection

Community detection is done using the generated network in section 3.1 in order to identify areas that are more connected compared to the rest of the nodes in the area, as well as identifying locations within or across the cities that exhibit co-behavior at a certain time of day.

In terms of mobility of cars, identifying these communities provide both spatial and temporal characteristics. In its spatial aspect, identifying the communities in the subject area provides the general shape of prevailing movement of the cars. Identifying the prevalent shapes in the communities formed may reveal an underlying structure of the city based on the mobility of cars. Observing the shapes of the clusters and relating it to existing road network may provide additional information on which roads act as boundaries to movement of cars. In its temporal aspect, changes in the shapes and size of the clusters across different hours-of-day may provide insight on which communities are highly affected by the hour-of-day, and which nodes are more likely to stick together regardless of the time. Comparing communities across different hours-of-day may give insight on which hours-of-day are more similar in form and effect and which are not.

In order to generate clusters that represent different levels of connectivity, filtering of trips was introduced to the network. Filtering is done using mean travel time and estimated travel distance to generate several networks representing travelling schemes for each hour of the day. After which, the filtered network is subjected to Infomap community detection algorithm. Infomap has been used as a community detection algorithm by several researches since it can handle directed graphs. Similar to this study, Liu, et. al. (2015) used Infomap for identifying community structures from the taxi trip information they obtained. The algorithm utilizes the map equation, which focuses on the definition of the movement of the random walker in the network.

Multiple clustering results were summarized by calculating the adjusted rand index (ARI) as shown in Equation 1. The equation compares two sets of clusters and calculates the similarity of the two clustering schemes. Finally, three levels of clustering were generated, representing how each cluster evolve and merge as filter values were increased. ARI is also used as means of comparing the similarity of clustering from one hour of the day (hod) to another, thereby identifying hours with similar traffic characteristics, or hour groups.

$$ARI = \frac{\Sigma_{ij}\binom{n_{ij}}{2} - \frac{\left[\Sigma_i\binom{a_i}{2}\Sigma_j\binom{b_j}{2}\right]}{\binom{n}{2}}}{\frac{1}{2}\left[\Sigma_i\binom{a_i}{2}\Sigma_j\binom{b_j}{2}\right] - \frac{\left[\Sigma_i\binom{a_i}{2}\Sigma_j\binom{b_j}{2}\right]}{\binom{n}{2}}} \qquad (eq. 1)$$

In the equation, the left part of the numerator, $\Sigma_{ij}\binom{n_{ij}}{2}$, corresponds to the rand index, while the right side, $\frac{\left[\Sigma_i\binom{a_i}{2}\Sigma_j\binom{b_j}{2}\right]}{\binom{n}{2}}$, is the expected value of the rand index from the random model, or the baseline correction. The rand index calculates the ratio of agreements over disagreements, while the baseline correction tries to remove the bias of rand index towards clustering schemes with high number of clusters. The value of the adjusted rand index falls between -1 to 1 where the sign of the index indicating whether the index value is above or below the expected chance. A value of zero means a random clustering.

4 RESULTS AND DISCUSSIONS

4.1 Communities from time and distance filters

Starting from the 2-minute time filter, Figure 5 shows an example of clustering results from the incremental time filter employed.

Figure 5. Clustering (indicated by blue polygons) for different time filters in 00 hour of the day

Observing the trend by changing the time filters, it is evident that as the time filter value is increased, the clusters became larger and consequently, the smaller the number of clusters there was. This can be attributed to the fact that using larger values of filter means that there are more trip data that are included in the graph. Additionally, these added trips have higher travel times to those trips that were included in the previous time filter. Generally, the added trips travel farther in terms of distance than the trips included previously. Eventually, adding a longer edge to the original graph makes a more connected graph.

Figure 6. Clustering (as indicated by red polygons) for different distance filters in 00 hour of the day

Figure 6 meanwhile shows the clustering scheme for distance filtering. Observing the similarities and differences of the two filters, the initial obvious difference is the granularity of clustering. For time filter clustering, clustering formed was very granular and multiple levels of clustering can be observed. Whereas for the distance filter, the created clusters were larger compared to the time filter clusters. Also, only three levels were generated before achieving the full connectivity, compared to the nine levels of clustering that was generated using the multiple time filters.

The evident difference between the two clustering scenarios is the clustering at the middle part of the study area. Mostly, the clusters generated from the distance filters were longitudinal in shape whereas the shape of the clusters formed from time filters are mostly horizontally oriented. The difference in shapes for both clustering in this area may suggest two things about the mobility of cars for this hour-of-day. The longitudinal direction of clusters for distance filter suggests that most cars have a north-south direction of movement for the central part of Metro Manila. This is because of the nature of the methodology employed in which the linear proximity of destination to its source point is the main factor in choosing which trips to include. In doing so, the clusters are forced to adapt to the direction in which most cars would go. Meanwhile, the horizontal orientation of clusters from the time filters suggests that the movement of cars in the east west direction is faster compared to other directions, as it has prevailed as the shape of the clusters. Since the main factor in this method is the travel time, the clusters will shape towards the direction where cars move the fastest.

It is also observed that comparing the clustering schemes from different hours of the day, different observations can be said for time and distance filter. For distance filters, across different hours of the day, similar observation is seen wherein the shape of the clusters are longitudinal suggesting a dominant North-South direction of movement. However, this is not true for time filters. Particularly, 2-min filters at different hours of the day shows that very few clusters are observed in hours like 08-12 as compared to earlier hours like 00-07, as shown in Figure 7 below. For earlier hours, clusters are dense, and some clusters formed are elongated in shape and follows the direction of the prevailing road that overlaps the cluster such as in Epifanio Delos Santos Avenue (EDSA), Shaw Boulevard, C-5 Avenue, Taft Avenue, Roxas Boulevard, Quezon Avenue, and Quirino Avenue. In succeeding hours, the clusters became more rounded from their elongated shape. Clusters along the said roads prevailed for later hours of the day and clustering in areas such as central Metro Manila became empty.

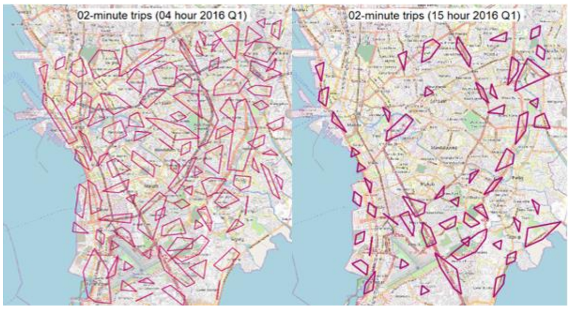

Figure 7. Comparing the 2-minute trips for 04 hour of the day (left) and 15 hour of the day (right)

4.2 Temporal Characteristics

Calculation of adjusted rand index is done to compare different filters and hours-of-day. It is noted that for each hour-of-day, the values of adjusted rand index fluctuate until a certain time filter value where the index value becomes high and stable. This stable time filter value is noted and graphed for all hours of the day in order to further aid in identifying similar hours. Figure 8 shows the graph of the stable time filter values.

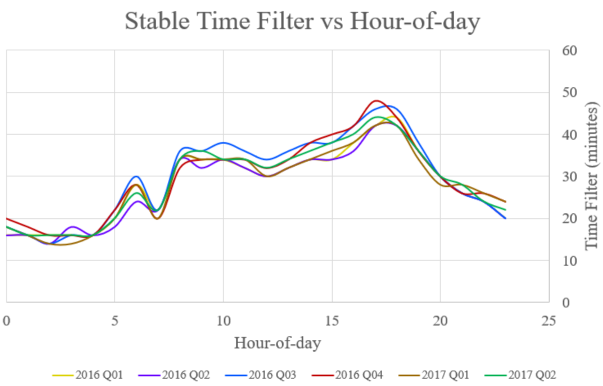

Figure 8. Stable time filter value of different hours of the day

Several characteristics can be observed from the ARI values as well as the graph in Figure 8. One of which is the low valued time filter for early morning hours. A low value stable filter suggests a better connectivity since this implies that trips of this time filter value create a well-connected network. A slight increase in stable time filter value is seen at 05 hod, then a peak at 06 hod which can be attributed to the start of morning rush. A dip can be seen in stable time filter value at 07 hod, in which number coding scheme starts. 07 hod stable time filter value is somewhat the same with the 05 hod value. For succeeding hours, the stable time filter value is the same and stable suggesting very similar traffic for these hours. A slight dip at 12 hod is seen which may imply an ease in traffic although very minimal. From here, the stable time filter value increases until a peak value at the 17th and 18th hours of the day. Afterwards, there is a constant decrease in the stable time filter value from 19 hod to 23 hod.

Table 1. Hour groups and their characteristics

Group	Hours-of-day	Remarks
1: large, dense cluster, high mobility, high	00, 01, 02, 03, 04	Low valued stable time filter
2: few cluster overlap defined roads	05, 06, 07	Peak in 06 hod, 05 and 07 similar
3: late morning, clusters smaller	08, 09, 10, 11, 12	Consistent valued
4: early afternoon, clusters fewer and smaller	13, 14, 15	Slight increase in stable time filter value
5: afternoon rush, clusters on eastern roads only	16, 17, 18, 19	High valued stable time filter
6: clusters similar to group 2 but denser	20, 21, 22, 23	Constant decrease of stable time filter

Clustering were summarized based on the grouping seen in Table 1. With this, Figure 9 shows the clustering scheme for different hour groups.

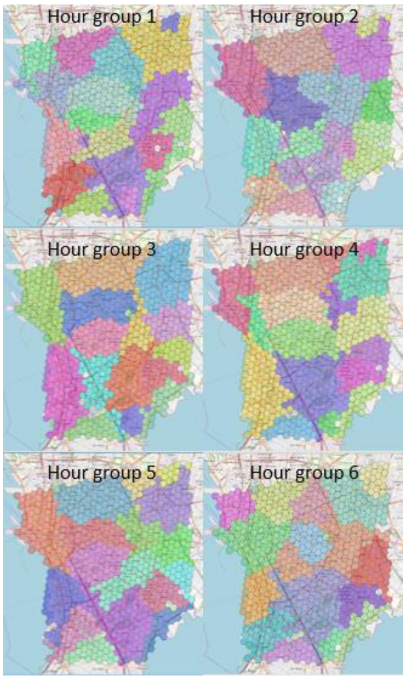

Figure 9. Clustering scheme for the six hour groups. Each color represents a cluster.

One noticeable information that can be seen in *Figure 9. Clustering scheme for the six hour groups*Figure 9 is that there are clusters that are prevalent or existing all throughout the six hour groups. One example of which is the cluster formed in the lower central area as shown in Figure 10. Further observing, this cluster is bounded by the Ninoy Aquino International Airport on its north and the Osmena Highway on its east. Its spatial configuration provided a heavy influence on its formation, and probably its persistence. The airport became one of the major barriers in car mobility going to and from this cluster as it hinders direct mobility from two opposite sides of the airport. Meanwhile, the Osmena highway also acts as a major blockage for this cluster.

Figure 10. An example of prevalent cluster (encircled in red) that appears in all six hourgroups.

Aside from persistent clusters, it can also be seen that some clusters are evolving in shape as in Figure 11. In this figure, two separate clusters from hour-group 1 comprised the larger clustering that is persistent from hour-group 2 to hour-group 5. This persistent cluster reverted back to two clusters that is very similar to hour group 1.

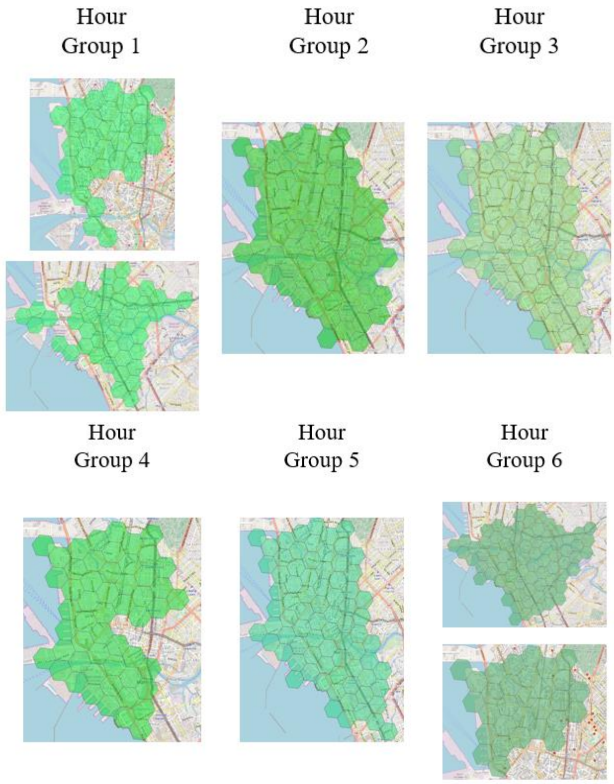

Figure 11. An example of evolving cluster across different hour groups.

4.3 Spatial characteristics

Some cluster shapes as observed are influenced by the roads that overlap the cluster. Generally, there are two roles of which major roads play in this configuration of clusters. The first one is being the skeleton of the cluster. This means that the road lies in the middle of the cluster and the major orientation of the road is adapted as the major shape of the cluster. This has been seen earlier in 2-min time filters where clusters are mostly elongated along the direction of major roads it overlaps.

Roads can also serve as boundaries between two clusters. This is the opposite of the skeleton role wherein the movement flows from the major roads propagating away or vice versa. In this case, major roads that act as boundaries can be literally seen near or at the boundary of the cluster. This means that the accessibility and connectivity is hindered into one side of the road.

Aside from roads, natural features such as water ways and river network along Metro Manila serve as barriers to connectivity. This means that these bodies of water prevent connections to the other side of the water body, which is expected. This can be compared to roads serving as boundaries to clusters, as mentioned previously. Roads that act as boundaries limit the movement as if there’s a water body hindering it from travelling.

Another noticeable feature or characteristics of the shapes of the clusters are its tails. This characteristic is not really evident in some clusters but for a few, this characteristic can be easily seen because of its unique shape. The tails of clusters indicate the dominant road which is often used to enter or exit the cluster. In other words, the tails act as gates to the cluster. In Figure 10b, the tail for this cluster is the Radial Road 10 inside the blue circle in the figure. The tail of this cluster act as the main location for providing access to and from the core of the cluster which is in the Tondo area.

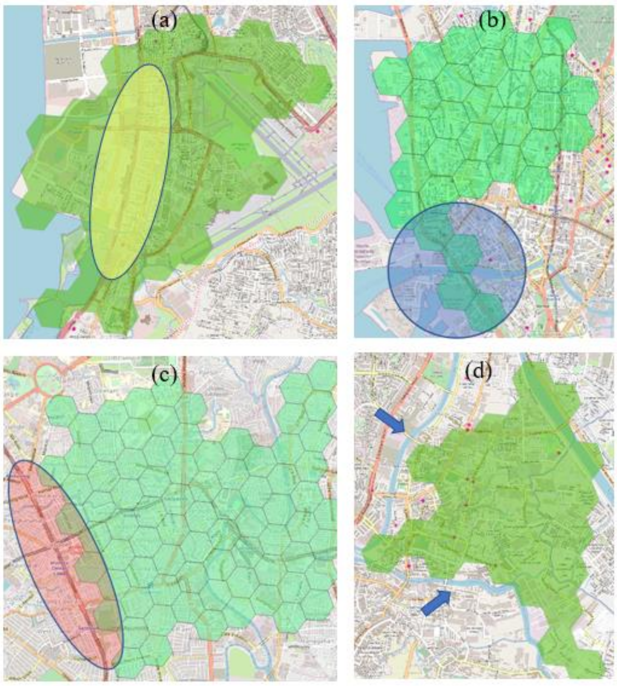

Figure 12. Common characteristics of clusters and its dependence on roads and water bodies are shown. Encircled are roads that relay important dependence on the clusters such as (a) Roxas boulevard (yellow) that acts as skeleton, (b) Radial road 10 (blue) that act as gates going to and from the cluster, and (c) East avenue (red) that acts as boundary of the cluster. Water bodies also act as boundaries such as (d) Marikina River and Pasig river that shaped the cluster as shown by blue arrows.

5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This research shows the effectiveness of utilizing network analysis in determining the characteristics and travel patterns of cars in Metro Manila. Network analysis has been an effective method in modelling trip information since ubiquitous location-based information are generally described using nodes as origin and destination, which is very similar to networks. Both the spatial and temporal characteristics of traffic were effectively extracted through observing clusters formed via Infomap algorithm. The clustering information can lead to a more dynamic Traffic Analysis Zones (TAZ) that traffic agencies are monitoring. These clusters have a good way of providing which areas are more similar and at different hours of the day. In doing so, the existing TAZs, which rely on administrative boundaries, will be more enhanced by identifying which barangays are very similar in traffic situation in the morning, and which should be managed differently in the evening.

5.2 Recommendation

The research can be expanded if the approach is problem-based wherein the focus is to identify the characteristics of car movement from different sources of data. Other location-based platform such as Waze or Grab, or even taxi GPS can be used as an additional source of information. In this way, there are more sources of data, and more samples of car mobility can be used for better characterization.

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