Measuring changes in travel behavior patterns due to rainfall on urban roads

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Abstract

Globally, climate change has caused increases in frequency, duration and rainfall intensity. High rainfall can cause flooding on roads that results in traffic jams, with travelers modifying their routes to avoid congestion. Collection of multiple data is necessary to understand travel behavior. Bluetooth is a short-range wireless technology that can quickly collect large amounts of data. Tracking sequences of Bluetooth-enabled devices including cell phones, headphones and in-car audio systems can be used to record the movement of vehicles within a network. Bluetooth tracking sequences may be incomplete or inconsistent due to data failure of the nodes and tracking devices. One solution is to cluster together similar Bluetooth tracking sequences. The deoxyribonucleic acid (DNA) alignment method was applied to identify similarity/distance distribution between Bluetooth tracking path group sequences. during rainy days, with results used to plan new routes.

Keywords: Trip behaviors, Rainfall, Sequence alignment, Bluetooth data

1. Introduction

Climate change has induced variations in the frequency, duration and intensity of global rainfall patterns. Extreme rainfall as a percentage of total rainfall has also significantly increased. Rainfall is forecast to increase by 9.65% between 2011 and 2099. [1]. Intense rainfall is now experienced in many developing cities that have undergone rapid urbanization such as Bangkok, Thailand located in the lowlands of the Chao Phraya River. The city is divided into two areas as Thonburi and Phra Nakhon. Thonburi is an upland area with a higher elevation than Phra Nakhon that slopes to the east as an easy to flood pan. In 1974, the urbanized area of Bangkok was more than twice the city size in the early 1960s. By 1974, as shown in Fig. **1**, urbanized Bangkok had spread to the fringes of the surrounding province

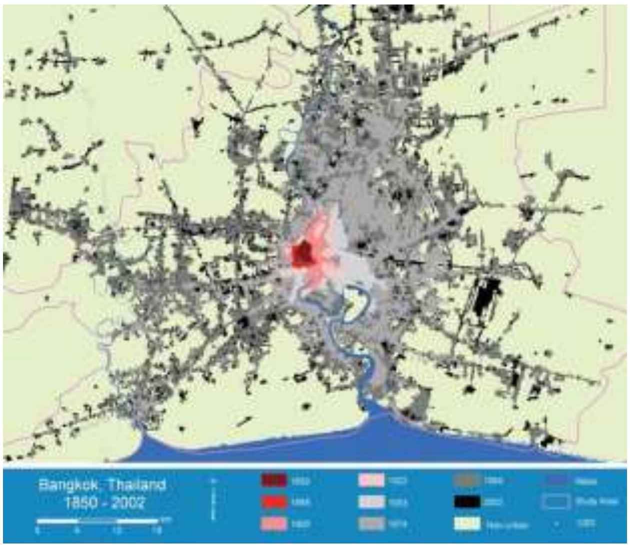

Fig. 1 The expansion of the Bangkok Metropolitan Region [2]

Urbanization involves complex mechanisms relating to urban land use characteristics [2], including the construction of housing estates, condominiums, and train lines. These infrastructures have impacted the original topography of Bangkok and now block the free flow of water through natural channels when heavy rain occurs. In fast-developing urbanization scenarios, drainage systems are often insufficiently developed and have and lack maintenance. Flooding disrupts surface infrastructure and transportation, with little time for the authorities and travelers to adapt to traffic disruptions. These issues have been previously addressed by integrating flood simulation and traffic analyses to model the interplay between these two spatiotemporal phenomena. Road networks have been modeled to assign new routes to combat the effects of road closures and evaluate travel delays. However, traffic distributions in these simulations were not as clear as expected [3]. The relationship between rainfall intensity and reduction in capacities and speeds of a road network has also been investigated [4-10], together with changing travel behavior in terms of demand [11, 12], traffic flow [13, 14] ,traffic safety [15, 16] and mode choice and departure time [17]. This dependence on behavioral adjustment provides policymakers with a deeper understanding of how rainfall conditions affect traffic.

Rainfall interrupts and delays all types of travel modes. Motorized vehicles have to reduce speed due to lack of visibility and this causes traffic congestion. Roads in low-lying areas often become impassable, forcing drivers to take alternative routes to reach their destinations. Rainy days influence travel behaviors by changing the travel paths that people take. Large-scale datasets are required to observe behavioral variations in travel. Gathering information was conducted using multi-day travel diaries [18], which are difficult to collect and incur high costs in terms of the respondent burden. These problems were solved by using GPS devices to measure day-to-day variability in travel behavior. The datasets provided larger measures of variability than those derived from traditional multi-day travel diary datasets. However, costs were high and surveys were often restricted to short time periods with small sample sizes [19].

With the recent increasing numbers of Bluetooth-enabled devices such as cellular phones, hands-free headsets, GPS and computers among road users, researchers proposed a novel cost-efficient approach to collect travel data using Bluetooth technology. Obtaining the unique Mac address allows repetition of trip-making behavior [29] and traveling schedules of the same device, unlike other sensor systems. Data were collected using fixed Bluetooth detectors installed next to roads by recording the unique identifiers of passing vehicles. The data was then matched across space and time by conversion into point-to-point path sequences to represent traveler movements in the study area. [30, 31]. The path sequences in the data were compared through a sequence alignment method (SAM) [32], also conducted in biological studies to measure the distance between DNA strings of protein strands.

This procedure infers the homologous positions within sequences [33]. Toward the end of the 1990s, sequence alignment was adapted for use in the social sciences to provide a quantitative measure of the similarity between character sequences, and also to represent daily activity patterns. Patterns obtained using sequence alignment offer a new way of improving understanding of travel behavior [34]. The same approach was used for Bluetooth detectors installed at strategic points within the study area. Whenever a Bluetooth-enabled device entered a node’s radio range, its MAC address was logged. Sequence alignment of the same MAC was then used to analyze the order of a visitor’s sequential movements or measure spatial variability of the path sequence [35-37].

This study focuses on understanding how rainy days influence the path choice behavior using Sequence Alignment method to measure the spatial variability of trips. The methodology of the proposed approach is outlined in Fig. 1. At first, the Bluetooth data from Bluetooth detector is exported from the database server as raw data that can be split into each trip sequence by MAC addresses, sequence trip corresponding to detection date, and time and duration of device being present in the detection zone. The trip sequences for all travelers are analyzed by sequences alignment method and then clustering is used for dividing path groups. Finally, the path group is analyzed to determine the travel behavior during non-rainy and rainy day conditions.

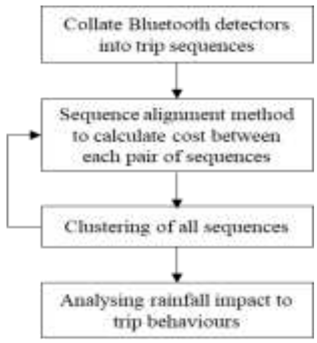

Fig. 2 Overview of the process using Sequence Alignment

2. Data collection

2.1 Rainfall data

Precipitation records were collected from the Thai Meteorological Department Bangkok weather station. The city receives over 2,000 mm of precipitation annually. shows raster maps from over 125 rain stations in Bangkok, comparing the amount of cumulative rainfall from January to April 2018. Rainfall was lowest (<250 mm) in the suburban area to the east of the inner city, while the highest cumulative rainfall (>450 mm) was recorded in the inner city and middle area or urban fringe area. Rainfall distribution was more spatially concentrated in the central business district (CBD), leading to an increased risk of urban waterlogging. Fig. 3 also shows a graph detailing the monthly rainfall of each rain station interpolated using the Thiessen polygon [38] to determine average precipitation over an area covering more than one measurement, The basic concept is to divide the watershed into several polygons, each one around a measurement point, and then take a weighted average of the measurements based on the size of each polygon. April had a cumulative average of 481 mm is the highest, while February recorded the least precipitation with an average of 48.6 mm

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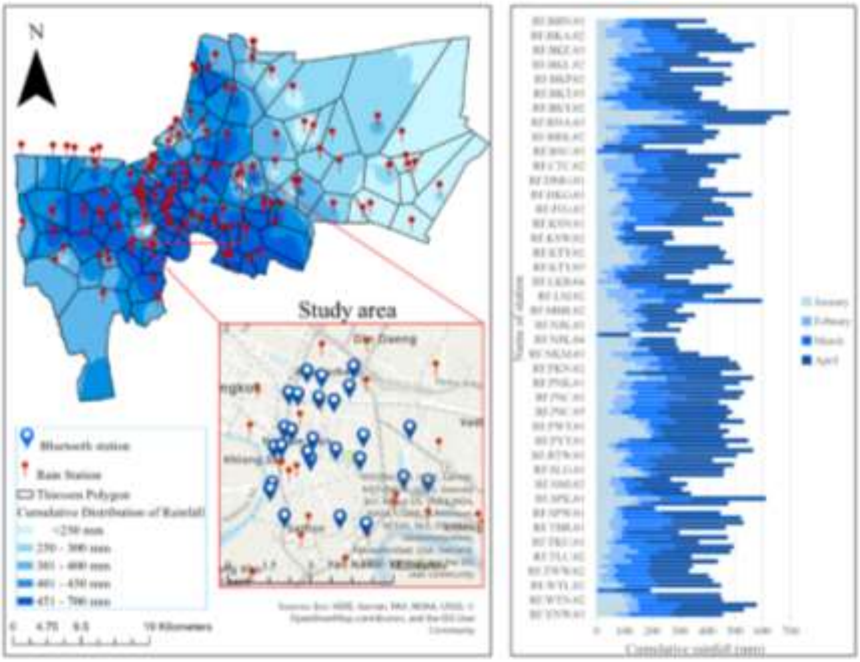


Fig. 3 Locations of Rainfall stations and Bluetooth detectors

2.2 Bluetooth data

The 26 Bluetooth detectors shown in Fig. 3 were deployed in police boxes at main road intersections to obtain traffic states such as origin-destination and congestion on road sections. Historical data to observe patterns of driving behavior, by accumulating driving routes on the spatial map and developing the methodology to manage trips using historical travel time, were collected between 14 January 2018 and 30 April 2018. Bluetooth detector data were exported from the database server as raw data as 39,5214 MAC addresses for analysis into 2,113,308 trips. The penetration rate which is the ratio of equipped Bluetooth device vehicle to the actual volume count, in this research has average about 5.22%. Therefore, a two percent match rate on a roadway of 100,000 AADT would provide more than enough hits to accurately generate mean travel times in five-minute intervals [39].

The Bluetooth detector data had some outliers that were removed using the Median Absolute Deviation (MAD) technique [20] before splitting to each trip [40]. The criteria for split trips considered both speed and travel time. In this study, we used the lowest speed as 2 km/hr, with travel time of more than 30 min for splitting each trip or the unusual situation such as car stopping or pedestrian walking, similar to Carpenter et al [41].

Testing parameters for generating trip-linking by Bluetooth detectors ranged from 5 to 60 min, with 30 min chosen as the most reasonable for corridors with maximum distance between adjacent sensor pairs of 1-5 miles. Longer time criteria for split trips used more Bluetooth detectors on a single trip, resulting in fewer total trips. Hence, in this study, 30 min was chosen based on the travel time. Samples of trips split into these criteria are shown in in Fig. 4.

order	BT. MAC address	Time	BT. Station	Time diff.	Speed (km/hr)
1	38:C0:96:76:BD:C0	21:29:01	48	0:03:51	11.22
2	38:C0:96:76:BD:C0	21:32:52	26	0:00:31	37.51
3	38:C0:96:76:BD:C0	21:33:23	33	-	-
4	38:C0:96:76:BD:D5	21:22:36	38	0:03:18	21.69
5	38:C0:96:76:BD:D5	21:25:54	12	0:12:46	2.66
6	38:C0:96:76:BD:D5	21:38:40	49	0:05:07	12.30
7	38:C0:96:76:BD:D5	21:43:47	35	0:01:45	5.11
8	38:C0:96:76:BD:D5	21:45:32	42	1:16:18	0.13
9	38:C0:96:76:BD:D5	23:01:50	35	0:01:31	6.73
10	38:C0:96:76:BD:D5	23:03:21	42	-	-

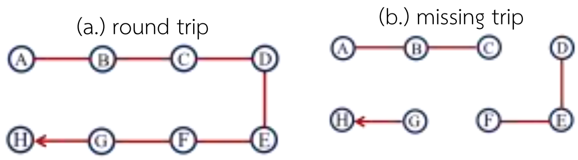
Trip 1
Trip 2
Trip 3

Trip 1 & Trip 2: Split by MAC address, it is different.

Trip 2 & Trip 3: Split by Time Interval or speed (not more than 30 mins or lower than 2 km/hr.

Fig. 4 Sample of trips that split by time and speed criteria.

A trip was defined as the route pattern of a unique MAC address detected from the origin point (start station) to the destination point (end of station), and then registered with corresponding details of date and time. The path of each traveler was registered based on the date and time of initial detection. Duration of time spent by the traveler when passing between the detectors also involved missed detections. These trips included “Complete trip” and “Missing trip”. A complete trip connected continuous stations and included single trip, missing trip, round trip and two-station trip, as shown in Fig. 5 a, b, c and d respectively.



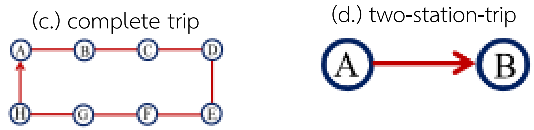


Fig. 5 Types of trip obtained from Bluetooth tracking.

Table 1 shows travel data results obtained from the Bluetooth detectors after removing outlier days (days with a low detection rate), yielding 92 days of observations containing 41 non-rainy days and 51 rainy days. Average number of trips made per day was 22,970, with an average of 7,000 paths as unique Bluetooth tracking sequences in the network area. On weekdays, average trips decreased 2-4%, except for Fridays, with an increase in travel during rain

Table 1 Travel data obtained by Bluetooth detectors.

Weekday	Trip average			Path average		
	Non-rainy	Rainy	Change(%)	Non-rainy	Rainy	Change(%)
Monday	23,371	22,409	4.12	7,516	7,292	2.99
Tuesday	24,422	23,457	3.96	7,904	7,517	4.90
Wednesday	25,153	23,544	6.40	7,597	7,597	8.17
Thursday	24,087	23,418	2.78	7,631	7,631	5.15
Friday	23,268	23,855	-2.53	7,688	7,688	1.88

3. Sequence alignment method

The alignment method followed the Needleman-Wunsch algorithm [42], as one of the first applications of dynamic programming used for optimal global alignment over the entire length of two sequences. Two paths for a sequence are compared alignment to observe patterns of variability or assess whether it is likely that two sequences evolved from the same sequence, which involves the construction of the best alignment between the sequences and assessment of the similarity from the alignment.

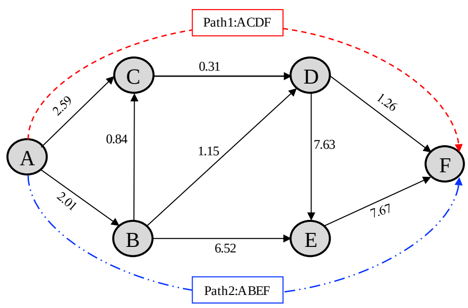


Fig. 6 Example of road network.

The simplest scoring scheme rewards matches and penalizes mismatches (substitutions) or gaps (indels). These values are half the distance between the two most distant detectors. The algorithm is best illustrated by the network shown in Fig. 6 as the simplest path to compare two sequences "ACDF" and "ABEF" of the same length. Fig. 5 gives rise to a 2D matrix representation as the score matrix and traceback. The cells of the score matrix are labeled *C(i; j)* where i = 1,2, ...,N and j = 1, 2, ...,M, as Fig. 7.

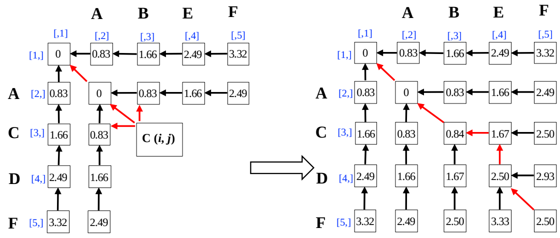


Fig. 7 Comparison of similarity scores for sequence alignment.

The first row and the first column of the indel score and traceback matrices are filled during the initialization. Indel is half of the distance between the A and F sensors when an indel of 0.83 was used. The score matrix cells are filled by rows starting from cell *C(2, 2),* the score of any cell *C(i; j)* is the minimum of up, diagonal and left, such that

$$C(i,j) = min\begin{cases} C(i-1,j)+g \\ C(i-1,j-1)+s(i,j) \\ C(i,j-1)+g \end{cases} \quad (1)$$

Where s(i, j) is the distance between the letters in position i and j, and g is the indel penalty. For calculation example in cell C(3, 3)

$$\mathrm{C(3,3)} = \min\begin{cases} \mathrm{C(2,3)+g} & = 0.83+0.83 = 1.66 \\ \mathrm{C(2,2)+s(C,B)} & = 0.00+0.84 = 0.84 \\ \mathrm{C(3,2)+g} & = 0.83+0.83 = 1.66 \end{cases}$$

Where C(2, 3), C(2, 2) and C(3, 2) are read from the score matrix, and S(C, B) is the score for the C to B taken from the shortest path. The minimum score in matrix C(3, 3) is 0.84, cells are filled. The best alignment via the algorithm is shown in Fig. 7. Finally, a quantitative measure of the similarity of "ABEF" compared to "ACDF" via the algorithm is shown in the Fig. 8, as a total cost of 2.5.

Match	Mismatch	Gaps (indels)								
A		**B**		**E**		**-**		**F**		
:		:		:		:		:		
A		C		-		D		F		
0	+	0.84	+	0.83	+	0.83	+	0	=	2.50

Fig. 8 The relationship between the cost of pairwise alignment.

Optimal alignments were calculated between all unique sequences to prevent duplication [43] using Abbot's normalization [32], which also accounts for sequences of different lengths.

$$\mathrm{normalized\ \ pairwis\ \ cost\ \ (x,y)} = \textstyle\sum_i \mathrm{pairwise\ \ cost(x_i, y_i)/i} \quad (2)$$

Where cost (x_i, y_i) is distance between the letters in position i in sequence x and y with a constant distance used between an indel and any letter, i is length of the longer sequence of the pair

4. Data Analysis Results

The trips were displayed in spatial map format as an overview of traffic patterns and density on each link. Fig. 9 shows the pattern and density of accumulated trips on weekdays. Highest traffic pattern density occurred on links along main roads in the downtown area of Bangkok. Results showed that some of the local routes incurred less time travel than the main routes. The characteristics of route choice behavior might not choose the best route as they lacked traffic trajectory information. The data assisted in understanding route choice in each area

Fig. 9 Illustration of trip pattern average on weekday.

Bluetooth detectors were logistically placed in fixed positions along different paths chosen by travelers, and detected for 92 days during the four month data collection period. Bluetooth detectors captured the start station and end station in the study area. Different path sequences in traveler detection were recorded during non-rainy days and rainy days. The spatial data diagram (Fig. 10) shows an example of the Mac address movement pattern (00:0A:3A:30:84:08) from node I to node Q. Sequences of all trips during the study period were superimposed on the sheet and split into rainy days and non-rainy days. On rainy days, travel patterns increased, suggesting that rain affected travel pattern behavior.

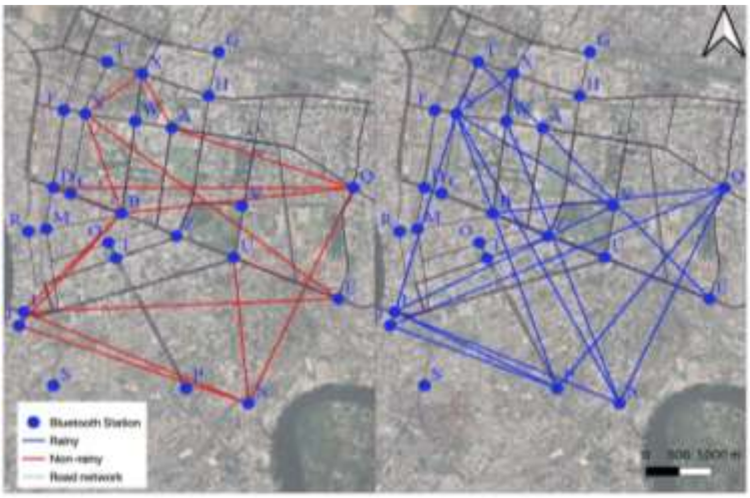


Fig. 10 OD pattern of unique Mac address between a non-rainy and rainy day.

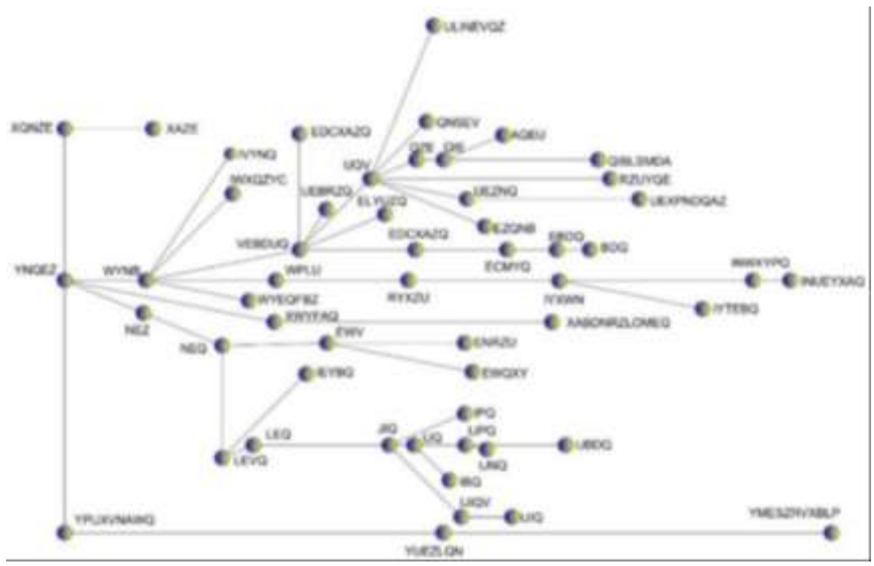


Fig. 11 Multiple alignment guide tree with clusters

Alignment of the whole database produced a tree graph (Fig. 11) that revealed locations visited and the order in which a traveler visited these locations. The nodes represent path sequences, while the edges of the graph are associated with the minimum score between two path sequences. Each path sequence was aligned separately to identify the greatest similarity. Throughout the 92-day study duration, 203 path sequence patterns were analyzed using pairwise sequence alignment to calculate similarity. The k-means values were then employed to cluster the path sequences into 11 path groups by observing the centroid vectors.

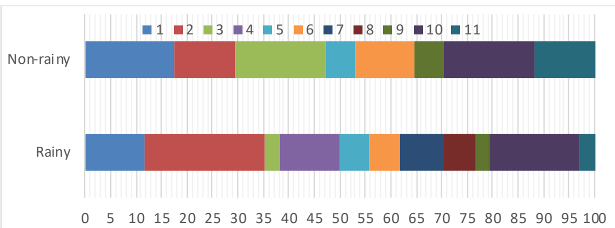


Fig. 12 The proportion of trips by each path group.

Fig. 12 shows the proportion of trips by path group from score of the greatest similarity which were used to consider path change behavior of traveler on rainy days. The results show that these proportions changed in group 3 and decreased by about 14 % during rainy days, while the travelers chose to use groups 4, 7, and 8 when travelling on rainy days. The distribution of trips between path groups was then used to assess the effect of spatial variability.

5. Conclusions

This research analyzed the distribution of rainfall in Bangkok between January and April. Results showed that the inner and urban fringe areas had cumulative average rainfalls of more than 450 mm at the end of April. Historical Bluetooth data were used to analyze trips consisting of 235,316 MAC addresses split into 1,398,329 trips. This problem was resolved using the sequence alignment method, which compares sequence similarities. Sequences of trips with similar scores were grouped.

Findings indicated that Bluetooth provided information on basic trends of traveler movements. Bluetooth data were used to consider the patterns and variability in individual behavior, using the sequence alignment method to extract similar movement patterns (path groups). The proportion of changes in each path group reflected the decision-making dynamics of each traveler and had a large effect on the evaluation of trip patterns during rainy days. These trip patterns described the activities and behaviors of travelers in the study area. Our results may help to anticipate the movement of travelers and also indicate the possibility of managing flow and congestion during rainy conditions. This is important for developing new, flexible and dynamic policies for space control, and modeling traveler response in various situations. The proportion result has changed in each path group to help the authorities reconsider measures for traffic management techniques and apply them prudently for each appropriate path group.

Acknowledgements

Assoc.Prof. Sarawit Narupiti from Faculty of Engineering, Chulalongkorn University, Thailand for Bluetooth data-Thai Meteorological Department for rainfall data.

Appendix

Table 2 Substitution matrix between each pair of detectors (shortest path,km)

O/D	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	0.00	2.01	2.59	2.83	4.88	1.66	2.85	2.10	5.04	5.03	6.25	2.69	3.40	6.48	2.43	5.03	3.01	3.83	5.39	1.90	2.92	2.39	0.58	2.47	1.33	2.90
B	2.01	0.00	0.87	1.15	6.52	2.41	3.77	3.36	3.29	3.29	7.75	1.02	1.61	5.41	0.77	3.37	4.98	2.04	3.64	2.82	1.86	2.26	1.50	3.39	2.18	0.94
C	2.59	0.87	0.00	0.31	7.34	1.58	4.25	3.85	3.03	3.02	8.57	1.86	0.81	6.23	1.60	4.20	5.60	1.24	3.38	2.21	2.68	3.08	2.07	2.79	1.31	1.76
D	2.83	1.15	0.31	0.00	7.63	1.26	4.49	4.09	2.90	2.90	8.86	2.14	0.68	6.52	1.83	4.49	5.85	1.11	3.25	2.45	2.97	3.36	2.32	3.02	1.56	2.05
E	4.88	6.52	7.34	7.63	0.00	7.67	7.95	7.49	7.05	7.05	6.02	5.33	6.86	2.47	5.46	3.89	3.71	7.21	5.93	8.11	4.98	4.37	6.79	8.68	7.44	6.23
F	1.66	2.41	1.58	1.26	7.67	0.00	3.26	2.86	4.16	4.16	7.89	3.39	1.95	7.77	3.10	5.74	4.65	2.38	4.51	1.22	4.21	4.03	1.10	1.79	0.33	3.30
G	2.85	3.77	4.25	4.49	7.95	3.26	0.00	2.46	7.02	7.01	7.51	4.74	5.05	9.09	4.49	7.09	5.25	5.48	7.37	2.03	5.53	4.89	2.25	2.60	2.93	4.62
H	2.10	3.36	3.85	4.09	7.49	2.86	2.46	0.00	6.48	6.47	6.35	4.09	5.29	6.91	4.21	6.21	3.14	5.72	6.83	2.47	3.66	2.52	2.47	3.04	3.22	4.79
I	5.04	3.29	3.03	2.90	7.05	4.16	7.02	6.48	0.00	1.70	9.49	2.37	2.15	7.15	2.55	3.82	6.97	2.15	2.05	5.23	4.26	4.48	4.77	5.80	4.32	4.21
J	5.03	3.29	3.02	2.90	7.05	4.16	7.01	6.47	1.70	0.00	9.46	2.35	2.12	7.13	2.52	3.80	6.94	2.12	2.02	5.20	4.23	4.45	4.74	5.77	4.29	4.18
K	6.25	7.75	8.57	8.86	6.02	7.89	7.51	6.35	9.49	9.46	0.00	8.24	9.62	7.07	8.37	8.08	3.27	10.05	10.17	7.97	7.69	5.94	6.80	8.54	7.55	9.12
L	2.69	1.02	1.86	2.14	5.33	3.39	4.74	4.09	2.37	2.35	8.24	0.00	1.71	5.55	0.33	2.46	5.12	2.03	2.74	3.89	2.00	2.39	2.57	4.46	3.06	2.02
M	3.40	1.61	0.81	0.68	6.86	1.95	5.05	5.29	2.15	2.12	9.62	1.71	0.00	6.60	1.27	3.93	6.17	0.79	2.57	3.08	3.05	3.45	2.69	3.65	2.18	2.13
N	6.48	5.41	6.23	6.52	2.47	7.77	9.09	6.91	7.15	7.13	7.07	5.55	6.60	0.00	4.13	1.50	4.44	5.83	3.54	7.69	5.04	4.43	6.38	8.26	6.86	5.82
O	2.43	0.77	1.60	1.83	5.46	3.10	4.49	4.21	2.55	2.52	8.37	0.33	1.27	4.13	0.00	2.65	5.18	1.75	2.95	3.59	2.06	2.46	2.27	4.16	2.75	1.71
P	5.03	3.37	4.20	4.49	3.89	5.74	7.09	6.21	3.82	3.80	8.08	2.46	3.93	1.50	2.65	0.00	5.21	4.38	2.09	6.24	4.35	3.98	4.93	6.81	5.41	4.37
Q	3.01	4.98	5.60	5.85	3.71	4.65	5.25	3.14	6.97	6.94	3.27	5.12	6.17	4.44	5.18	5.21	0.00	6.84	7.43	4.77	4.48	2.74	3.59	5.34	4.34	5.91
R	3.83	2.04	1.24	1.11	7.21	2.38	5.48	5.72	2.15	2.12	10.05	2.03	0.79	5.83	1.75	4.38	6.84	0.00	2.86	3.37	3.34	3.74	2.98	3.94	2.47	2.42
S	5.39	3.64	3.38	3.25	5.93	4.51	7.37	6.83	2.05	2.02	10.17	2.74	2.57	3.54	2.95	2.09	7.43	2.86	0.00	6.29	4.76	4.97	5.27	6.86	5.39	4.71
T	1.90	2.82	2.21	2.45	8.11	1.22	2.03	2.47	5.23	5.20	7.97	3.89	3.08	7.69	3.59	6.24	4.77	3.37	6.29	0.00	4.67	4.12	1.39	0.57	0.91	3.76
U	2.92	1.86	2.68	2.97	4.98	4.21	5.53	3.66	4.26	4.23	7.69	2.00	3.05	5.04	2.06	4.35	4.48	3.34	4.76	4.67	0.00	1.42	4.27	6.02	5.02	3.92
V	2.39	2.26	3.08	3.36	4.37	4.03	4.89	2.52	4.48	4.45	5.94	2.39	3.45	4.43	2.46	3.98	2.74	3.74	4.97	4.12	1.42	0.00	2.88	4.63	3.64	3.24
W	0.58	1.50	2.07	2.32	6.79	1.10	2.25	2.47	4.77	4.74	6.80	2.57	2.69	6.38	2.27	4.93	3.59	2.98	5.27	1.39	4.27	2.88	0.00	1.89	1.53	3.13
X	2.47	3.39	2.79	3.02	8.68	1.79	2.60	3.04	5.80	5.77	8.54	4.46	3.65	8.26	4.16	6.81	5.34	3.94	6.86	0.57	6.02	4.63	1.89	0.00	3.05	4.74
Y	1.33	2.18	1.31	1.56	7.44	0.33	2.93	3.22	4.32	4.29	7.55	3.06	2.18	6.86	2.75	5.41	4.34	2.47	5.39	0.91	5.02	3.64	1.53	3.05	0.00	3.07
Z	2.90	0.94	1.76	2.05	6.23	3.30	4.62	4.79	4.21	4.18	9.12	2.02	2.13	5.82	1.71	4.37	5.91	2.42	4.71	3.76	3.92	3.24	3.13	4.74	3.07	0.00

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