Calculating Total Delivery Times from Service Time Distribution

Kenji TANAKA¹, Kenji ARAOKA¹, Shen-ming GU²,* and Jing ZHANG²,*

¹Department of Systems Innovation, The University of Tokyo, Tokyo, Japan
²Key Laboratory of Oceanographic Big Data Mining & Application of Zhejiang Province, Zhejiang Ocean University, Zhoushan, Zhejiang 316022, China

*Corresponding author

Keywords: Delivery time, Service time, Cluster.

Abstract. This study aims to improve the efficiency of last-mile delivery by quantifying service time and estimating delivery time based on service time distribution. We present a method to increase delivery efficiency.

Introduction

The size of the electronic commerce (EC) market continues to rise. The global business-to-consumer (BtoC)-EC market USD 1,920 billion in 2016, a 23.7% increase compared with the previous year. For China, the United States, and Japan, the EC conversion rates were 15%, 11%, and 6%, respectively, and they are expected to continue to grow in the future. Furthermore, in the global consumer-to-consumer (CtoC)-EC market, taking marketplace app Mercari as an example, sales in the fiscal year ending June 2016 increased to USD 120 million, a 189% increase from the previous term. With the growth of the EC market, the logistics industry, especially last-mile delivery, is expected to have to cope with an unprecedented high level of demand [1-2]. For example, same-day and next-day delivery services have become the industry standard. In addition, scheduled delivery of packages in a time slot selected by the customer is becoming necessary.

Therefore, research on efficient logistics services and system construction is required, particularly on quantifying and estimating delivery time, which are crucial building blocks for constructing efficient logistics and delivery services. To quantify the service time, Ashbrook & Starner [3][4] used the k-means method, Palma et al. [5] and Adams, Phung & Venkatesh [6] used the DBSCAN algorithm, and Kurashima et al. [7] used the mean shift to determine delivery bottlenecks. Furthermore, Nurmi & Bhattacharya [8] proposed a nonparametric Bayesian method. However, because these methods considered only distance information, they did not have a high resolving power when visiting the same area repeatedly at different times and dates. The vehicle routing problem is often discussed for estimating delivery time. For example, Li, Tian & Leung [9], Duyug et al. [10], and Binart et al. [11] investigated the travel time or service time and the probability density function, and they formulated delivery routes considering the specified time as a constraint on the uncertainty of the required time. However, because the probability density function cannot be obtained by analyzing real data, this method is not practical.

In this research, we quantify service time and estimate delivery time based on service time distribution. Furthermore, we present a method that may help to construct efficient delivery systems.

Delivery Time and Service Time

We use actual delivery data on a logistics company collected by an industry-academia cooperative and divide the last-mile delivery data into four stages of wide-area movement between the sales offices and the point of delivery: movement between areas, movement within the area, transfer to customer, and waiting. Figure 1 shows the composition of the time taken for each component of last-mile delivery. Movement between sales offices and areas refers to movement between the sales office and the delivery area. Movement within the area refers to the movement of the delivery truck in the

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delivery area. Transfer to customer refers to the driver parking, taking the package from the truck, handing the package to the customer, and returning to the truck. Standby refers to the driver waiting in the truck with no delivery until a specified time. The total time in this research is the travel time, transfer-to-customer time, and waiting time.

The transfer-to-customer time is particularly important and its variation is large compared with the travel time and waiting time. Therefore, we quantify and estimate the delivery time first. The flow for the estimation method is shown in Figure 2.

**Estimation of Service Time Distribution**

In estimating the service time distribution for each customer, GPS and delivery record input data are used to clarify the probability distribution. GPS data are position information data recorded by portable terminals mounted on the truck and carried by the driver. The delivery record data are records of the deliveries to the customer, consisting of the delivery time and location. The proposed method consists of four steps.

Determine dwell points based on the GPS data. We apply a two-step clustering method to extract multiple dwell points in one GPS data set.
Use delivery history data from among multiple retention points to match each delivery. Calculate service time for each delivery. First, the service time is calculated considering the driver's waiting behavior. In addition, when several deliveries are made when the truck is parked, the service time per case is calculated.

Steps 1–3 are repeated to calculate all service times for the entire period. Furthermore, the calculated service time is linked to customers to estimate the probability distribution of delivery service times for each customer.

**Proposal and Application of Two-Stage Clustering Method**

We confirmed the noise, loss, and robustness to loss of the GPS data, and adapted the two-step mean shift method. The whole flow for the method is shown in Figure 3.

![Flow for two-step clustering method dwell point extraction](image1)

First, GPS longitude, latitude, and time information are converted into three-dimensional data (Figure 4). Clustering by a one-step mean shift is performed according to the interval distance of the converted three-dimensional data.

![Conversion of an image to 3D data](image2)

Next, based on only the position information, a search for clusters close to the Euclidean distance is performed, and clustering is carried out by a two-step mean shift (Figure 5).

![Set of staying points](image3)
Furthermore, clusters with a time difference less than or equal to one another are combined to prevent fragmentation of the dwell point due to noise from arbitrary lengths. The residence time is determined as the dwell point and subsequently extracted.

**Estimation of Waiting Time**

The parking and waiting behaviors are estimated from the extracted dwell points. First, a list of dwell points based on the GPS data of the truck is linked to the delivery result data to estimate the parking behavior. Then, by associating the estimated parking behavior with the list of dwell points based on the driver’s GPS data, the standby behavior is estimated. For all actions, binding is determined based on the distance and time.

**Estimating Customer Service Time Distribution**

Based on the data in the previous sections, we determine the service time distributions of individual customers (Figure 6).

**Calculation of Total Delivery Time**

The total required time is calculated as the sum of the wide-area travel time, in-area travel time, and total service time. The wide-area travel time is calculated from the actual data as the distances to the first and last customers. In addition, the in-area movement time is calculated by an approximation of the in-area movement distance, expressed by Equation 1.

\[
d_{area} = \alpha \sqrt{n} + \beta \cdot d_{ave_g} \cdot Cmp_{area} + \gamma
\]

Where:
- \(d_{area}\) = Travel time in a delivery area [s]
- \(n\) = Number of customers
- \(d_{ave_g}\) = Customer centroid distance [m]
- \(Cmp_{area}\) = Complexity of a delivery area
- \(\alpha, \beta, \gamma\) = Regression coefficients
Conclusion
To improve the efficiency of last-mile delivery, we quantified the service time and proposed a method to estimate the total delivery time. In the future, we intend to verify and improve our research method with industry-academia collaboration company data.

Acknowledgement
The research was funded by the National Science Foundation of Zhejiang Province No.LY18G010016.

References