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A robust transfer inference algorithm for public transport journeys during disruptions

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Abstract

Disruptions in public transport have major impact on passengers and disproportional effects on passenger satisfaction. The availability of smart card data gives opportunities to better quantify disruption impacts on passengers' experienced journey travel time and comfort. For this, accurate journey inference from raw transaction data is required. Several rule-based algorithms exist to infer whether a passenger alighting and subsequent boarding is categorized as transfer or final destination where an activity is performed. Although this logic can infer transfers during undisrupted public transport operations, these algorithms have limitations during disruptions: disruptions and subsequent operational rescheduling measures can force passengers to travel via routes which would be non-optimal or illogical during undisrupted operations. Therefore, applying existing algorithms can lead to biased journey inference and biased disruption impact quantification. We develop and apply a new transfer inference algorithm which infers journeys from raw smart card transactions in an accurate way during both disrupted and undisrupted operations. In this algorithm we incorporate the effects of denied boarding, transferring to a vehicle of the same line (due to operator rescheduling measures as short-turning), and the use of public transport services of another operator on another network level as intermediate journey stage during disruptions. This results in an algorithm with an improved transfer inference performance compared to existing algorithms.

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Keywords: Disruptions, public transport, smart card data, transfer inference

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1. Introduction

Disruptions in public transport can have a major impact on passengers' nominal and perceived journey travel time. The operation of public transport services without disruptions is considered a key quality aspect of public transport by passengers (Golob et al., 1972; Van Oort, 2011). Therefore, it is important to get insight in passenger behaviour during disruptions. Passive data availability the last decades provides an opportunity to get more insight in this. Automated fare collection (AFC) data, automated vehicle location (AVL) data, and data from automated passenger count (APC) systems sources are used for many purposes by scientists and practitioners on a strategic, tactical and operational level (Pelletier et al. 2011). Passive data availability allows a comparison of the realized journey travel time during a disruption with the undisrupted travel time on an individual level, and therefore allows quantification of disruption costs.

A first important requirement for this comparison is that journeys can be inferred in a valid way. When no valid distinction is made between transfers and destinations, this can result in a biased journey identification and thus a biased journey level quantification of disruption impacts. Last decade several studies are performed to estimate origin-destination (OD) matrices based on individual AFC transaction data (see for example Trépanier et al. 2007; Zhao et al. 2007; Seaborn et al. 2009; Wang et al. 2011; Munigaza and Palma 2012; Gordon et al. 2013; Nunes et al. 2016). These studies propose advanced algorithms to infer journeys from passive data for regular circumstances. However, these algorithms are based on a certain logic in passenger route choice. For example, when the next transaction is made in the same public transport line as the previous transaction, current algorithms infer an activity since there is no other reason why passengers would alight a vehicle and then board a next vehicle of the same line again (Gordon et al. 2013). However, during disruptions passengers might have to adjust their route choice due to limited service availability, which can result in routes which would be illogical in case there were no disruptions. For example, due to operator rescheduling measures as deadheading or short-turning during disruptions, passengers might have to make an additional transfer to the subsequent vehicle of the same line. This means that the logic on which current transfer inference algorithms are based is not suitable to infer transfers during disruptions, given the illogical route and transfer choice passengers might be forced to during disruptions. Applying existing algorithms leads to biased transfer inference and thus to a biased OD matrix estimation. As a consequence, quantifying disruption costs on an OD level will be biased as well.

To be able to infer transfers during disruptions therefore places additional challenges to transfer inference algorithms, since these algorithms must be robust to infer transfers during disruptions, while still providing valid results for undisrupted situations as well. This is necessary, since it is often difficult to infer the exact time demarcation between disrupted and undisrupted circumstances from disaggregated AVL and AFC data sources. This research develops such transfer inference algorithm. Chapter 2 discusses the methodology. The developed algorithm is applied to a case study, of which results are presented in chapter 3. Conclusions and recommendations for further research are formulated in chapter 4.

2. Methodology

2.1. The Hague case study network

In our study we use passive data from HTM, the urban public transport operator of The Hague, The Netherlands. The urban network in The Hague consists of light rail, tram and bus lines. The set of public transport lines is denoted by L . Each public transport line $l \in L$ is defined as an ordered sequence of stops $S_l = (s_{l,1}, s_{l,2}, \dots, s_{l,|l|})$. Each line $l \in L$ is operated by an ordered set of runs (run sequence), denoted by R_l . A run $r \in R_l$ is performed by one vehicle serving the ordered stop sequence S_l in one direction. For each run $r \in R_l$ there exists a schedule with scheduled arrival times \tilde{t}_a and departure times \tilde{t}_d for each stop $s_{l,j} \in S_l$.

When travelling in light rail, trams or busses in The Netherlands by smart card, passengers are required to tap in and tap out at devices which are located within the vehicle. This means that the passenger fare is based on the exact distance travelled in a specific public transport vehicle. Especially for busses, this is different from many other cities in the world where often an open, entry-only system with flat fare structure is applied, for example in London (Gordon et al. 2013) and Santiago, Chile (Munigaza and Palma 2012). This means that for each individual

transaction the boarding time and location, and the alighting time and location of each journey stage are known. Also, it is known in which public transport line, vehicle number and trip number (a unique number assigned to each one-directional run $r \in R_l$) each passenger boarded with their unique smart card number. The AVL data provides the scheduled times \tilde{t}_a and \tilde{t}_d , and the realized times t_a and t_d for each run at each stop, where each run is indicated by the same trip number as appears in the AFC data. By integrating AFC and AVL data based on the corresponding trip number, vehicle occupancy can be inferred for each run between each stop $s_{l,1}, s_{l,2}$.

2.2. Full validation of destination inference algorithm

Before starting the analyses, data cleaning and data processing is required. First, transactions where a system error occurred are removed from the dataset. In these cases there occurred an error in the AFC devices, leading to unrealistic alighting times or alighting locations, or to missing or unrealistic trip numbers. For The Hague, this percentage varies between 0.05% and 0.50% of the daily transactions. The closed within-vehicle AFC systems means that in general destinations of journey stages are directly available from the data, so no destination inference is needed. Therefore, destination inference needs to be performed only for transactions where there was a missing tap out. This occurs when passengers unintentionally forget to tap out when alighting from the vehicle, or deliberately do not tap out if the distance based travel costs are higher than the deposit deduced from the card when boarding for relatively long trips. The daily percentage of transactions with a missing tap out in The Hague varies between 1% and 2% on average. For destination inference we apply the well-known trip chaining algorithm as applied by Trépanier et al. (2007), Zhao et al. (2007) and Wang et al. (2011). The aim is to estimate the alighting stop \hat{s}_{pjk}^a of the j th journey stage of the total number of journey stages m made by passenger p on day k . The indices s^a and s^b reflect the alighting and boarding stop, respectively. The following basic assumptions as applied in this algorithm:

- If $m > 1$ and $j \neq m$: the most likely alighting location of j is the stop which is closest to $s_{p(j+1)k}^b$.
- If $m > 1$ and $j = m$: the most likely alighting location of j is the stop which is closest to $s_{p(j=1)k}^b$. Assumed is that passengers return to the location where the first journey stage started (e.g. home) at the end of the day.
- If $m = 1$: trip chaining is not possible and no destination can be inferred. In that case, the transaction is removed from the dataset. Contrary to Trépanier et al. (2007), we did not incorporate travel behavior made by the same card number on previous days in the algorithm. Since destination inference is not the main research goal of this study, we aimed to prevent too much noise in the dataset from complex destination inference algorithms.

The set of candidate stops A_{pjk} for \hat{s}_j^a in case $m > 1$ and $j = m$ is shown by Eq.(1) and contains all stops from the registered boarding stop s_l^b at line l downstream to $s_{l,|l|}$. In case $m > 1$ and $j \neq m$ an additional constraint is added, which guarantees that the realized arrival time t_{as} of run r at stop s should be earlier than the boarding time at s_l^b of the next journey stage $j + 1$. This is expressed by Eq.(2).

$$A_{pjk} = \{s_{lj}^b \dots s_{lj}^+\}, j < m_{pk} \quad (1)$$

$$A_{pjk} = \{s_{lj}^b \dots s_{lj}^+\}, j = m_{pk} \quad st. t_{asrj} < t_{dsr(j+1)} \quad (2)$$

The selection of \hat{s}_{pjk}^a from A_{pjk} is based on minimizing the Euclidean distance d between the candidate alighting stop and $s_{p(j+1)k}^b$ or $s_{p(j=1)k}^b$. We minimize the Euclidean distance, instead of the generalized travel time as proposed by Munigaza and Palma (2012) and Sánchez-Martínez (2017). Using generalized travel time is mostly beneficial if the set of candidate stops contains stops of a public transport line in both directions. Minimizing the Euclidean distance could then infer a stop of the line in the opposite direction which is just slightly closer to the next boarding location, while neglecting the substantially longer in-vehicle time to reach that stop. Since our candidate set is one-directional and only contains stops downstream the boarding location, we can minimize the Euclidean distance without problems. A maximum walking distance threshold d_{walk} is applied. If no candidate stops can be found within a reasonable walking distance, it is likely that this passenger used another mode as intermediate journey stage. In that case no destination can be inferred. Eq.(3) shows the applied destination inference algorithm.

$$\hat{s}_{pjk}^a = \operatorname{argmin}\{d(s_{p(j+1)k}^b, \hat{s}_{pjk}^a)\} \quad \forall \hat{s}_{pjk}^a \in A_{pjk}, m_{pk} > 1 \quad st. d \leq d_{walk} \quad (3)$$

Validation of the applied destination inference algorithms shows to be difficult in other studies. Inferred destinations can be validated with passenger counts in vehicles or at stops, or by using surveys to a small sample of the population. Besides, a variety of walking distance thresholds is applied, varying between 400m (Zhao et al. 2007), 750m (Gordon et al. 2013), 1000m (Wang et al. 2011; Munizaga and Palma 2012) and 2000m (Trépanier et al. 2007). The fact that in the Dutch urban public transport network both tap in and tap out are required, however enables a full validation of the algorithm and allows the selection of an optimal value for d_{walk} resulting in the most accurate destination inference. We selected all complete transactions made on the HTM network on one working day ($\approx 286,000$ transactions) and removed the alighting location. We applied the destination inference algorithm with varying values for d_{walk} to predict back these alighting locations and considered the percentage of destinations what was correctly, incorrectly and not inferred, respectively. Table 1 and Figure 1 provide the results. From Table 1 can be seen that, depending on d_{walk} , in total between 70% and 87% of all destinations could be inferred. This is higher than percentages found by Trépanier et al. (2007) and Zhao et al. (2007) ranging between 66% and 71%. The higher d_{walk} , the more destinations could logically be inferred. However, with an increasing number of inferred destinations the number of incorrectly inferred destinations increases faster than the number of correctly inferred destinations. From all inferred destinations, the percentage correctly inferred drops from 71% for $d_{walk}=200$ to 65% for $d_{walk}=1600$. This shows there is a trade-off between the quantity and accuracy of inferred destinations.

Table 1. Destination inference results for varying values of d_{walk}

Variable	d_{200}	d_{400}	d_{600}	d_{800}	d_{1000}	d_{1200}	d_{1400}	d_{1600}
% inferred destinations	69.6%	76.4%	80.6%	83.2%	84.5%	85.6%	86.1%	86.6%
% correctly inferred from all inferred destinations	70.6%	70.1%	68.3%	66.9%	66.1%	65.7%	65.4%	65.1%
% correctly inferred from total transactions	49,1%	53,6%	55,0%	55,6%	55,9%	56,2%	56,3%	56,4%
% incorrectly inferred from total transactions	20,5%	22,8%	25,5%	27,5%	28,6%	29,4%	29,8%	30,2%
% not inferred from total transactions	30,4%	23,6%	19,4%	16,9%	15,5%	14,4%	13,9%	13,4%

To find the optimal d_{walk} , we maximize the number of correctly inferred destinations $\hat{s}_{pjk}^{a,c}$ corrected for incorrectly inferred destinations $\hat{s}_{pjk}^{a,w}$, as shown by Eq.(4). We increased d_{walk} stepwise by 200m starting from 200 to 1600 Euclidean meters. Figure 1 shows that this value is maximized when applying a maximum walking threshold of 400 Euclidean meters (on average ≈ 550 real meters). For $d_{walk}=400$ we investigated the error margins for a subset of 100 transactions. For 72% of wrongly inferred destinations, the chosen destination was only 1 stop further upstream or downstream. This probably reflects passengers performing an activity between two stops and selecting the stop on the other side of the activity for boarding again.

$$d_{walk} = \operatorname{argmax}(\hat{s}_{pjk}^{a,c} - \hat{s}_{pjk}^{a,w}), d_{walk} \{d_{200}, d_{400}, \dots, d_{1600}\} \quad (4)$$

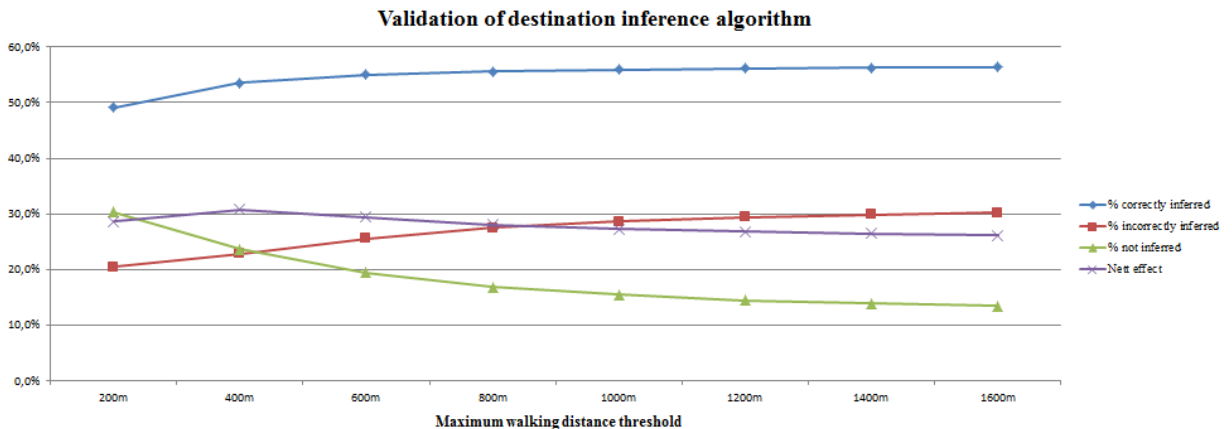


Fig. 1. Performance of destination inference algorithm for different maximum Euclidean walking distance values

2.3. Robust transfer inference algorithm

We show the state-of-the-practice and state-of-the-art transfer inference algorithms and then illustrate limitations of these algorithms based on a theoretical network. The state-of-the-practice criterion to identify an alighting as transfer as applied in The Netherlands is based on a maximum time threshold between the previous tap-out and next tap-in with the same smart card ID. If the time between t_{asrj} and $t_{dsr(j+1)}$ is larger than a transfer threshold time $t_{t,max}$, the alighting is classified as activity. In The Netherlands, $t_{t,max}=35$ minutes. This criterion can lead to biased transfer inference, mainly because it tends to underestimate short journeys. If activities are performed which last shorter than 35 minutes, two separate journeys are incorrectly considered as one journey. If this is a back-and-forth trip of which $s_{pjk}^b = s_{p(j+1)k}^a$, this journey is not included in the OD matrix at all. Given the high frequent services in urban public transport, a transfer time of 35 minutes will not often be exceeded. During disruptions longer transfer times are however also possible, which could also overestimate the number of journeys.

When considering state-of-the-art transfer inference algorithms, three criteria are formulated which should all be satisfied to define an alighting as transfer.

- Temporal criterion. The temporal constraint as applied in practice is replaced by a criterion which expresses whether a passenger took the first passing vehicle at a transfer, by integrating AFC and AVL data (Gordon et al. 2013). Based on t_{apjk} and the stop coordinates of the alighting stop and next boarding stop, the first realistic passenger arrival time at the next boarding time can be calculated. In this study, we correct the Euclidean distance by $\sqrt{2}$ to obtain realistic transfer distances. We use the 2.5th percentile of the walking speed distribution derived by H  nseler et al. (2016) instead of the average walking speed, to prevent that on average 50% of transferring passengers might not be considered as transferring. The first realistic passenger arrival time at the next boarding stop is compared with realized vehicle departure times of the chosen line. If the first passing vehicle after the first realistic passenger arrival time is taken, the alighting is considered a transfer. A minimum transfer allowance of 5 minutes is applied.
- Spatial criterion. The spatial criterion constrains the maximum transfer distance to d_{walk} . In this study we set d_{walk} to 400 Euclidean meters, in line with results from chapter 2.2.
- Binary criterion. The binary constraint is whether the next boarding line is equal to the previous boarding line. In this case, alighting is considered a activity. Successive services in opposite direction indicate a return trip from an activity, whereas successive services in the same direction also indicate a performed activity (Gordon et al. 2013).

We adjust this state-of-the-art algorithm to make the algorithm robust to transfer inference during disruptions. To illustrate the relevance of this algorithm, we use a selection of the HTM case study network as shown in Figure 2. It shows a light rail connection between the center of the satellite city Zoetermeer (nodes A-B on the left) via intermediate stop D to the center of a main city (nodes F-G on the right). There is also a separate transit line between D-E. The public transport lines A-B-D-F-G (line 4), C-B-D-F-G (line 3), and D-E (line 19) are operated by the same operator (HTM). This means that both AFC and AVL data from these lines is available. Stops C and F provide transfer connections to the train network, which stations are indicated as C1 and F1. The train service C1-F1 is operated by another operator, which means that only AVL data (open data in The Netherlands) is available.

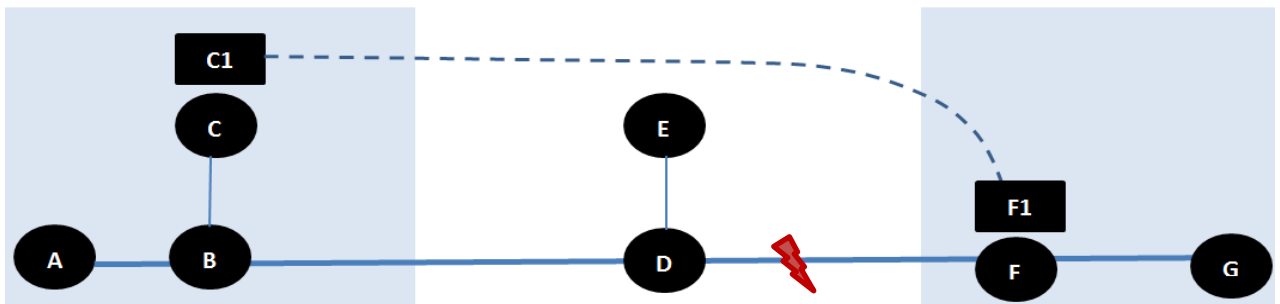


Fig. 2. Selection of The Hague case study public transport network

We assume a disruption (e.g. a signal failure) occurs on the light rail track between D and F, leading to reduced capacity between D and F. In line with HTM disruption management, 50% of the light rail services eastbound short-turns at D, whereas 50% of the westbound light rail services short-turn at F. We consider three different passenger journeys over this network, shown by Table 2.

Table 2. Illustration new transfer inference algorithm for three OD journeys E-G, B-G and A-G

Boarding stop	Alighting stop	Smart card ID	Transit line	Transfer?	Transfer?
				<i>Current algorithm</i>	<i>New algorithm</i>
E	D	1233	19	No	Yes
D	G	1233	3		
B	C	1234	3	No	Yes
F	G	1234	4		
A	D	1235	3	No	Yes
D	G	1235	3		

- Temporal criterion. We consider a journey from E to G. Due to reduced services between D and F, remaining vehicles can get very crowded. This means that transferring passengers at D (from E) can experience denied boarding in busy urban networks and might not be able to board the first passing vehicle. It is also possible that some passenger decide to wait for a next service, if they perceive the very crowded vehicle arriving at the station. Applying the original temporal criterion would therefore incorrectly classify the alighting of these passengers at D as activity, since they did not take the first passing vehicle. Under regular circumstances, denied boarding in The Netherlands is very exceptional. However, in disrupted situations the frequency of denied board and very crowded vehicles increases substantially. To account for this we adjust this criterion such that an alighting is considered a transfer, if a passenger takes the first *reasonable* passing vehicle at a transfer location. Boarding a reasonable vehicle is quantified by adding an extra constraint to the temporal criterion. An alighting is considered a transfer if a passenger boards the first vehicle of a service after the first realistic passenger arrival time at the stop, of which the occupancy is lower than the norm capacity. By integrating AFC and AVL data, vehicle occupancies are derived. When occupancies are higher than the norm capacity, it can be expected that passengers decide to skip this vehicle or are even denied boarding.
- Spatial criterion. We consider a journey from B to G. These passengers adjust their route choice, by using the train network at the side of the city centers as alternative. By transferring from C to C1, and back from F1 to F, the disruption is avoided. Especially in dense urban networks, passengers can use the total multi-level public transport network which remains available after a disruption (see e.g. Cats et al. 2016). Since train services are operated by another operator, no AFC data of this journey stage is available. Since the distance between C and F is substantially larger than common values for d_{walk} (in this study 400m), applying the original spatial criterion would incorrectly classify the alighting at C as journey destination and categorize the trip F-G as new journey. Since urban public transport is fully covered by AFC data, there is only the higher level train network as multi-level alternative which is not covered in the data. Therefore, we add a binary indicator to each stop which equals 1 if a train station is located within the maximum transfer distance d_{walk} . If both s_{pjk}^a and $s_{p(j+1)k}^b$ are equal to 1, we apply the temporal condition as explained above. We determine, given the train AVL data, whether the boarding time of a passenger in the urban network in F shows that this passenger took the first reasonable train alternative from C1 to F1. If the realized boarding time at F does not exceed the expected travel time given the realized train departure and arrival times, it is likely that another public transport mode is taken as intermediate journey stage. The alighting at C is then considered a transfer. A further relaxation of the original spatial criterion is applied, by considering a tap out and consecutive tap in to the same vehicle and trip number as transfer, even if the transfer distance exceeds d_{walk} . This indicates that a passenger did not really alight the vehicle, but (un)intendedly tapped out and in during the ride. This can be explained by passengers in doubt if the tap in was successful, holding their card to the device again and then tapping out.

Another explanation are passengers who deliberately tap out during a part of the trip to save travel costs, given the fully distance based fare.

- Binary condition. We consider a journey from A to G. A part of the passengers who keep using the light rail service have to alight their short-turning vehicle at D and wait for a next service of this line headed for G. This means that the disruption forces these passengers to make a transfer to the same line 3. The original algorithm would therefore incorrectly infer the alighting at D as journey destination. We therefore adjust the algorithm such that when a transfer to the same line is made, this is considered a transfer if and only if a passenger boards the first run of this same line after the alighted run. This allows transfer inference in case of rescheduling measures as short-turning, stop-skipping or deadheading. By only allowing the first run after the alighted run as transfer, in high frequency urban networks the headway will be short. Measures as short-turning or deadheading are in practice especially performed if the next run already bunches behind the previous one. This means that false positive transfer inferences are very unlikely, since the time to perform an activity will be very short. This adjustment is also relevant in case part of the disrupted track is replaced by bus services operating under the same line number. Besides, this adjustment can be of relevance during undisturbed situations in case of non-typical route typologies in which transfers to the same line number occur. For example, in case of lines with loops or in case of lines where short-services are operated under the same line number, it can occur that passengers have to transfer to a vehicle of the same line under planned circumstances.

3. Results

We compare the performance of the state-of-the-practice, state-of-the-art and newly developed transfer inference algorithm. To this aim, we use a dataset containing individual AFC transactions during two different non-recurrent disruptions which occurred on the HTM network in November 2015. The dataset contains transactions from passengers who specifically travelled over one of the disrupted lines and disruption location, during one of these disruptions (in total $\approx 23,300$ transactions). We applied the three different transfer inference algorithms to this dataset. For the state-of-the-practice algorithm we used a maximum transfer time of 35 minutes. For the state-of-the-art and new developed algorithm we set d_{walk} equal to 400 Euclidean meter. Based on a normal distributed walking speed $N(1.34, 0.34)$ we applied a 2.5th percentile walking speed of 0.66 m/s (Hänseler et al. 2016).

Table 3. Performance comparison between three different transfer inference algorithms

	State-of-the-practice	State-of-the-art	New developed algorithm
Average # trips per journey	1.44	1.18	1.21
% journeys with 0 transfers	68%	85%	82%
% journeys with 1 transfer	23%	14%	15%
% journeys > 3 transfers	0.8%	0.0%	0.1%

Table 3 shows that the algorithm as currently applied in practice results in a relatively high number of trips per journey (1.44), indicating that alighting is relatively often classified as transfer. This is because of the applied transfer threshold time without further behavioral rules. In the case study network, journeys with more than 3 transfers are almost not possible. Only additional transfer behavior during disruptions could require more than 3 transfers in total in rare occasions. Given that 0.8% of all journeys have more than 3 transfers, it shows that this state-of-the-practice algorithm overestimates transfer behavior. The state-of-the-art algorithm on the other hand shows less transfers and no journeys with more than 3 transfers. However, this algorithm is too strict in classifying an alighting as transfer, especially in case of disruptions.

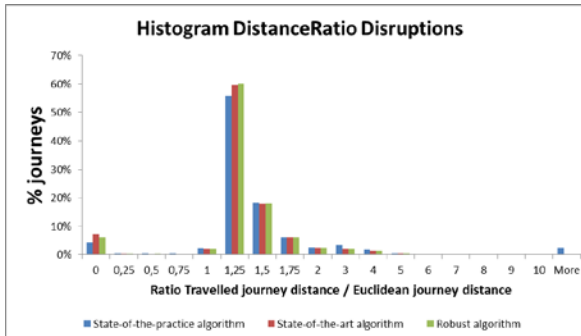


Fig. 3. Distribution of ratio travelled/Euclidean distance for state-of-the-practice, state-of-the-art and new robust transfer inference algorithm

In our developed algorithm there is some relaxation of the transfer criteria of the state-of-the-art algorithm. This results in a slightly higher average number of trips per journey (1.21 instead of 1.18). As shown in chapter 2.3, this new developed algorithm results in an improved transfer inference during disruptions. Besides, it also shows that still hardly journeys with > 3 transfers are identified when applying this new algorithm, despite these relaxations.

Figure 3 expresses the ratio between travelled distance by public transport and the Euclidean distance per identified journey. Journeys with a very high ratio are symptom for two separate journeys which are incorrectly identified as one (i.e. a back-and-forth travel identified as one journey). Thus, this ratio can be used to validate the performance of transfer inference algorithms. As can be seen, both the state-of-the-art and new algorithm prevent journeys with unrealistic high ratios, which are found using the state-of-the-practice algorithm. Our new proposed algorithm thus improves transfer inference during disruptions, without compromising on general inference quality.

4. Conclusion

Several rule-based algorithms exist to infer whether a passenger alighting and subsequent boarding is categorized as transfer or final destination where an activity is performed. Although this logic can infer transfers during undisrupted public transport operations, these algorithms have limitations during disruptions: disruptions and subsequent operational rescheduling measures can force passengers to travel via routes which would be non-optimal or illogical during undisrupted operations. We developed a new transfer inference algorithm which infers journeys from raw smart card transactions in an accurate way during both disrupted and undisrupted operations. In this algorithm we incorporate the effects of denied boarding, transferring to a vehicle of the same line, and the use of public transport services of another operator on another network level as intermediate journey stage during disruptions. A further validation of the proposed transfer inference algorithm is recommended for future research.

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