Multi-mode Trip Information Recognition Based on Wavelet Transform Modulus Maximum Algorithm by Using GPS and Acceleration Data

Fei Yang, Ph.D., Professor
School of Transportation and Logistics
Southwest Jiaotong University
No. 111 North Second Ring Road, Chengdu, Sichuan 610031, China
Tel: 86-135-500-25963
Email: yangfeitraffic@gmail.com

Zhenxing Yao*, Ph.D., Research Associate
School of Transportation and Logistics
Southwest Jiaotong University
No. 111 North Second Ring Road, Chengdu, Sichuan 610031, China
Tel: 86-158-285-19097
Email: yaozhenxingtraffic@163.com

Peter J. Jin, Ph.D., Assistant Professor,
Department of Civil and Environmental Engineering, Rutgers University
Rutgers, The State University of New Jersey,
Core 613, 96 Frelinghuysen Road, Piscataway, NJ 08854, USA
Tel: 1-848-445-8563
Email: peter.j.jin@rutgers.edu

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* Corresponding Author

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ABSTRACT

GPS-based travel survey is an emerging data collection method in transportation planning. Its application in trip mode detection has been explored in many existing studies. However, most existing research on GPS data based trip mode detection methods are developed and tested with data collected from European and American countries. Their methods cannot be easily adapted to Asian countries such as China, India, and Japan with much higher population density, the complex road network, and the highly-mixed travel modes during daily commuting. Furthermore, when conducting trip segment division in a multi-mode travel, the existing algorithms use travel time and distance thresholds which are highly dependent on the local travel behavior and lack universality across different traffic environment. This paper proposes an innovative framework to detect trip modes under complex urban environments. First, a smartphone application, named GPSurvey, is developed to collect passive GPS trace data. Then the Wavelet Transform Modulus Maximum (WTMM) algorithm is developed for trip segment division. WTMM has outstanding capabilities of identifying singularity features of a signal which suits the task of detecting mode changes in complex traffic environment. A neural network (NN) module is further developed for mode detection based on cell phone GPS location and acceleration data. Results indicate that the proposed method has a promising performance. The average absolute detection error of mode transfer time is within one minute, and the accuracy for detecting all modes is above 85%.

Keywords: Trip Mode, Wavelet Transform Modulus Maximum, Neural Network, GPS Trajectory, Acceleration
INTRODUCTION

Due to the urban expansion and functional division, travel patterns of individuals in major metropolitan areas around the world show significantly variations both in time and space, especially in Asian countries. In urban areas with high population density and complex traffic environment, people’s daily travel is usually executed through a combination of various modes. Traditional data collection methods like paper questionnaire, telephone interview and mail inquiry show the drawbacks due to the decreased response rate with the increased memory burden and data quality issues such as missing short trips (1, 2), reporting trips out of sequence (2, 3) and rounding up the departure and arrival times (4). Recently, several existing studies have explored the potentials of using GPS data to derive personal trip information. Studies have been conducted in European and American countries (1, 4-10). However, the travel patterns in tested cases are relatively simple. Passenger car is the main trip mode and the transferring among multiple modes are not often. Such methods have difficulties when directly applied to the urban centers in Asian countries with high population density and complex traffic environment. This paper attempts to develop an efficient mode data collection and identification method suitable for Asian urban centers.

Over the last decade, the potentials of GPS technology in assisting travel survey have received significant attention from researchers. GPS-based travel survey can provide more accurate, dynamic, and real-time representation of travel behaviors than traditional survey methods (3, 11, 12). Meanwhile, GPS devices can automatically record individual travel trajectories instead of through respondents’ memory. The devices can reduce the burden of survey tasks on respondents (13, 14). Recently, the increased popularity of smartphones has brought new opportunities for the practical use of GPS-based survey methods. By using Location Based Service (LBS) in smartphones, a large amount of travel trajectory data can be collected with almost no extra cost and at high location accuracy.

GPS data can provide information such as origin-destination, route choice, travel speed but cannot directly provide travel mode information which is crucial in transportation planning. In the existing methods (8, 10, 15), using GPS trajectory data to detect trip mode mainly includes two steps. At the first step, according to different travel destinations, GPS trajectories are divided into trips and then into mode-specific trip segments. At the second step, the pattern detection algorithm is applied to identify the trip mode.

Most previous studies use travel time and distance thresholds for trip segment division. Different thresholds have been used in different studies. For example, thresholds are defined for the dwelling time between two consecutive in-motion data points to determine trip end, different values used in existing study include 120s (16), 180s (8), or 300s (9). Similarly, different distance thresholds are seen in existing studies including 150m (17), 250m (15) and 500m (5) for trip segment detection. Empirically identifying threshold values largely depends on the specific situation of the study area and threshold values from one study cannot be directly transferred to another study. In recent years, the Wavelet Transform Modulus Maximum algorithm has been used to investigate various traffic-related issues, such as automatic detection of freeway incidents (18), traffic flow
forecasting (19, 20), traffic state monitoring (21-23), and driving behavior judgment (24). WTMM algorithm shows superior capabilities in analyzing singularity features of a signal which suits the task of detecting mode changes in complex traffic environment. In this study, WTMM algorithm is applied to the mode detection in GPS trajectory data.

Existing algorithms for trip mode detection are primarily data mining algorithms including learning-based algorithms (25, 26), regression algorithm (27), rule-based algorithm (28) and so on. Results showed the difficulty of distinguishing between car-based or bus-based trip by only using GPS data due to their identical characteristics. Some researchers considered using GIS data as an aid to improve the trip mode detection accuracy (5, 7, 8, 10, 16). In 2006, Tsui and Shalaby compared the mode detection based on GPS-only data and GPS with GIS data in a fuzzy logic-based mode detection algorithm. Results showed that GIS data improved the bus detection ratio from 76% to 80% (5). However, most other GPS+GIS data based studies only achieve a bus detection ratio below 70% (8, 10, 15). In 2013, Feng used GPS data combined with accelerometer data for mode detection (29), the study found that the acceleration can help improve mode detection accuracy. A limitation of the study is the focus on trips with uniform trip mode rather than trips with mixed travel mode under multi-modal urban environment.

In this paper, we proposed a GPS and accelerometer data based travel mode detection method for multi-modal environment. A smartphone application, named GPSurvey, is developed to collect multi-mode travel data. Special multi-mode travel tests consist of walking, bicycle, bus, car, and subway are conducted in the city of Chengdu, China. The WTMM module is adapted for the division of trip segments, and a NN module is further developed for mode detection.

**METHODOLOGY**

This section introduces the process and methods of trip mode detection using WTMM algorithm and NN algorithm. The WTMM algorithm divides travelers’ each multi-modal travel trajectory into single-mode trip segments according to the modulus maximum lines defined for the mode transferring. Then, the NN algorithm identifies the trip mode of each trip segment.

**Wavelet Transform Modulus Maximum Algorithm**

The WTMM algorithm is found to be an effective tool in signal processing because of its promising capabilities of detecting irregular structures and singularities of a signal. In this paper, if considering GPS speed as a signal sequence, the data characters of mode changing points are similar to signal singularities, which is well-suited for WTMM algorithm. WTMM algorithm detects singularities in two steps: singularity recognition and identification result denoising.

**Singularity Recognition**

The singularity of a signal is well-defined in the area of mathematics. If a signal $f(t)$ has mutations or discontinuous derivatives at some points, we define the signal as singularity. Generally, Lipschitz(Lip) exponent can be used to describe the singularity of a signal $f(t)$.

Assuming there is a non-negative integer $n$, $n \leq \alpha \leq n+1$, if there exists a constant $A>0$
and a polynomial of degree $n$, $p_n(t)$, such that for $t \in (t_0 - \delta, t_0 + \delta)$,

$$
\left| f(t) - p_n(t-t_0) \right| \leq A |t-t_0|^\alpha
$$

(1)

then $f(t)$ is described as “meeting Lip $\alpha$ at the point of $t_0$”. If the exponent of Lip at $t_0$ is smaller than 1, then we treat $t_0$ as the singular point of $f(t)$. The modulus maxima points of wavelet transform can also reflect the signal singularities. The relation between modulus maxima points and signal singularity is as follows:

Under a certain scale of $a_0$, if a point $(a_0, b_0)$ satisfies

$$
\frac{\partial W_f(a_0, b_0)}{\partial b} = 0
$$

(2)

then the point $(a_0, b_0)$ is a local extremum point. If the following condition is met.

$$
\left| W_f(a_0, b) \right| \leq \left| W_f(a_0, b_0) \right|
$$

(3)

where $b$ is within neighborhood of $b_0$. Then $(a_0, b_0)$ is defined as a modulus maximum point. A line connecting all the modulus maxima points in the scale of frequency $(a, b)$ is named the modulus maximum line.

In mode transfer time detection, when a traveler changes his or her trip mode, the volatility of travel speed generates singularities. Modulus maxima lines are expected to occur in the time-scale plane at each mode transfer point. When the analyzing scale is small, the mother wavelet oscillates and attenuates rapidly, and the modulus maxima points can have accurate time orientation for singularities. When the analyzing scale increases, the wavelet itself expands, the mother wavelet will reduce the oscillation frequency, and the time orientation of modulus maxima points for singularities becomes poor (30). Therefore, the modulus maxima points under small analyzing scale are used in trip mode detection. In the proposed model, the mode transfer time is obtained by finding the corresponding time points at the intersection of the modulus maxima line and the time axis where the analyzing scale is the smallest.

However, in field data multiple modulus maxima lines may correspond to the same mode transfer. In practice, the selection of a suitable wavelet function has a positive impact on mode transfer time detection. The vanishing moment is defined as follows. If a wavelet $\psi(t)$ satisfies

$$
\int_{-\infty}^{+\infty} t^k \psi(t) dt = 0
$$

(4)

for all $k < n$. Then $\psi(t)$ is said to have $n$ vanishing moments. The number of modulus maxima lines increases linearly with the number of vanishing moments. On one hand, too many modulus maxima lines can cause confusion for mode transfer time detection. On the other hand, when the maximum Lip exponent of a signal is $n$, the wavelet should have at least $n$ vanishing moments so that the biggest Lip exponent value can be detected. In this study, multiple trial experiments indicate that a wavelet with one vanishing moment is enough for modes transfer time detection. In addition, the accuracy of the singularity recognition time is also taken into consideration when choosing the optimal wavelet function.
**Detection Result Denoising**

The WTMM algorithm can effectively detect mode transfer point but it is not prune to false detection. For some secondary characteristic signals or noise signals of the GPS trajectories, for instance, vehicles stops at intersections or in congestion, the WTMM algorithm may misidentify these phenomena as car-walk transfers. Therefore, denoising the detection results is necessary.

The relationship between the wavelet modulus maxima $|w_{a,f}(x)|$ and the Lip exponent $\alpha$ is as follows. Suppose $\alpha \leq 1$, $f(x)$ has consistent Lip exponent on $[a,b]$, then there exists a constant $k > 0$, such that, when $x \in [a,b]$, the wavelet function satisfies the following inequality

$$ |W_a f(x)| \leq ka^a $$

Taking logarithm of both sides of formula 5, it follows that

$$ \log |W_a f(x)| \leq \log k + \alpha \log a $$

where $a$ stands for wavelet transform scales.

Equation 6 shows that if $\alpha > 0$, the modulus maxima increases with the increasing of scale; while if $\alpha < 0$, the modulus maxima decreases with the increasing of scale. The singularity exponent is always bigger than zero while noise exponent is always smaller than zero. With singularity and noise presenting opposite properties under multi-scale wavelet transform, the singular point denoising can be accomplished by removing those points whose amplitudes decrease with the increase of the scale. The denoising requires to set a relatively large value for the initial scale of the wavelet transformation in WTMM algorithm to eliminate the impact of noises or secondary characteristics. The smaller scale should then be used to obtain accurate time orientation of modulus maxima lines. Finally, the time corresponds to the intersection of modulus maximum line and time axis is the true mode transfer time.

**Neural Network (NN) Algorithm**

Different trip modes have different travel trajectory features, for example, the travel speed of car and bus are almost always larger than bicycle or walk. The stopping frequency of buses is also almost always higher than cars while traveling on the same route. Therefore, the key link in trip mode detection is to explore the parameters that reflect the main characteristics of different trip modes. In this paper, The NN model is applied for mode detection because of its superior nonlinear pattern recognition capabilities. An NN contains the input layer, the hidden layer, and the output layer. It can adapt to input–output data pairs and learn their underlying patterns through cycles of training in the hidden layer. A trained network can predict the output (mode) based on new input GPS data.

In the proposed NN algorithm, the average speed per minute, maximum speed per minute are used as the first two neural network input attributes to capture the general speed difference between trips by motorized vehicles and those by walking and bicycle. Meanwhile, the standard deviation of speed per minute represents the difference of how each mode responds to congested traffic. Motorized vehicle modes are more sensitive to
traffic congestion than walking and bicycling. The last feature is the standard deviation of
acceleration per minute which reflects the stability of acceleration in different modes.
These four attributes are used as neural network input attributes. The detailed neural
network topology for mode detection is shown in FIGURE 1.

![Diagram](image)

FIGURE 1: Detailed neural network topology for mode detection.

The WTMM algorithm divides each travel trajectory into trip segments with only
one travel mode. The most probable mode type for each divided segment is then
identified through neural network. It should be noted that this method does not account
for subway detection because no GPS data can be collected when traveling underground.
Subway mode can be identified by examining whether the previous trip ends in the
vicinity of a subway station and the beginning of the following trip starts near a subway
station. Other data sources such as subway IC card data can also be used to detect subway
mode directly.

DATA COLLECTION

In this paper, a cellphone GPS and accelerometer based mobile application, named
GPSurvey, is developed to collect multi-mode travel data. The cell phone GPS module
can continuously collect real-time data include GPS trajectory data such as Date, Time,
Latitude, Longitude, Speed, number of satellites and so on for every second, and the cell
phone accelerometer can continuously record three-dimensional acceleration along the x,
y and z axes every second. The detailed GPSurvey data collection interface and the user
interface are shown in Figure 2.

The data collection work was conducted in the downtown area of Chengdu city,
China. Chengdu has a population of more than 14 million, and it is a representative urban
area with high population density and complex traffic environments in China. In this
study, special multi-mode travel tests consist of walking, bicycle, bus, car, and subway,
are conducted in Chengdu. Detailed modes in each trip include Walk-Bus-Walk,
(including bus transfers at the same platform and different platforms),
Walk-Bus-Walk-Subway-Walk, and Walk-Bicycle-Walk-Bus-Walk. The sample size of
each basic multi-mode trip is 50 trips. The data collection routes are selected match
approximately with the subway line 1, 2 of Chengdu. Twenty volunteers from Southwest
Jiaotong University participated in the data collection.

FIGURE 2 The data collection interface and the user interface of GPSurvey. (a) Data collection interface; (b) User interface

MULTI-MODE TRAVEL FEATURES ANALYSIS

Different trip modes have different trajectory features. FIGURE 3 shows profiles of different multi-mode trips, (a) Walk-Bicycle-Walk, (b) Walk-Subway-Walk, (c) Walk-Bus-Walk, (d) Walk-Car-Walk. It can be seen that the walking speed ranges from 0 to 8 km/h, the bicycling speed is from 10 to 20 km/h, the average speed of the bus mode is about 25km/h, and the average speed of the car mode is 40km/h. No data were collected for subway mode due to the loss of GPS signal while traveling underground. In addition, the fluctuating frequency of bus speed is larger than car speed due to the frequent stopping at bus stops.

Furthermore, at trip mode transfer points, the travel speed drops to zero immediately. This large fluctuation of speed can lead to the signal singularity. However, when traveler stops at signalized intersections or bus stops, the travel speed also drop quickly, secondary signal characteristic points or noisy data will be generated. The signal fluctuation of secondary signal characteristic points and noisy data is usually temporary, for example, the car speed rises immediately after the stop at the intersection; while the speed changes are always permanent for the mode change.

FIGURE 3 also illustrates that different modes have different average speed, max speed and speed fluctuation range. FIGURE 4 shows the acceleration fluctuation features (standard deviation of acceleration per minute) of travel samples in FIGURE 3. It can be seen that walking has the most fluctuating profile, followed by subway, bicycle, bus and
This phenomenon is because that the relative body dispositions while walking is quite large compared with other modes. Based on the empirical analysis, this paper selects the average speed, the max speed, the standard deviation of speed and acceleration per minute as neural network training parameters to reflect the main characteristics of different trip modes.

**FIGURE 3** Speed examples of multi-mode travels.

(a) Walk-Bicycle-Walk; (b) Walk-Subway-Walk; (c) Walk-Bus-Walk; (d) Walk-Car-Walk

**FIGURE 4** Acceleration standard deviation per minute of multi-mode travels.

(a) Walk-Bicycle-Walk; (b) Walk-Subway-Walk; (c) Walk-Bus-Walk; (d) Walk-Car-Walk

**RESULT ANALYSIS**

**Results of Mode Transfer Time Detection**

The wavelet functions considered in this paper include Haar, the Daubechies family (D(n),
where \( n \) is the order of the Daubechies wavelet and the Gaussian family (Gaus(n)). The Complex Gaussian (1) which performs best in mode transfer time detection is used in this paper. FIGURE 5 displays the detection results of a Walk-Bicycle-Walk-Bus-Walk trip, FIGURE 5(a) shows the original GPS velocity profile of the sample data; FIGURE 5(b) shows the result of the wavelet transform modulus under different analysis scales. FIGURE 5(b) illustrates that the modulus is significantly larger (brighter) at the trip mode transfer points than elsewhere. FIGURE 5(c) shows the modulus curve under the specific scale of 150. It is clear that wavelet transform modulus obtain maximum at mode transfer points. FIGURE 5(d) shows the detection result of modulus maxima lines under different scales. Modulus maxima lines only occur at mode transfer points when the scale is set relatively large. Finally, the sample trip is divided into five trip segments, each segment contains a single mode.

Using the same method, FIGURE 6 demonstrates detection results of several representative multi-mode trips. FIGURE 6(a) is a Walk-Car-Walk trip. FIGURE 6(b) is a Walk-Subway-Walk trip. FIGURE 6(c) is a Walk-Bus-Walk-Bus-Walk trip (bus transfer at different platforms). FIGURE 6(d) is a Walk-Bus-Bus-Walk mode trip (bus transfer at the same platform). The results prove that the WTMM algorithm is efficient in the detection of mode transfer points.

FIGURE 5 Mode transfer points detection result of a Walk-Bicycle-Walk-Bus-Walk trip sample. (a) original velocity profile; (b) modulus atlas under different scales; (c) modulus curve under the scale of 150; (d) detection results of modulus maximum lines.
FIGURE 6 Mode transfer points detection result of representative multi-mode trips. 
(a) Walk-Car-Walk; (b) Walk-Subway-Walk; (c) Walk-Bus-Walk-Bus-Walk (bus transfer at different platforms); (d) Walk-Bus-Bus-Walk (bus transfer at the same platform)

TABLE 1 shows the error statistical results of mode transfer time detection. Since walking usually acts as a link between two other modes, the accuracy of WTMM based mode transfer point detection can be summarized by different mode-switching pairs (called transfer patterns) as shown in TABLE 1. The average error of all the mode transfer patterns is within 1 minute. Data quality is substantially improved when compared with traditional questionnaire survey, whose transfer time detection error usually reaches tens of minutes due to the rounding by the interviewees. Besides, the unidentified or misidentified transfer points (namely the ‘Failed’ column) among all the transfer patterns are below 5%. Most unidentified transfers happen between walk and bicycle modes. Walking is the linking mode between bicycling and other modes in this study, and the duration of the transitional walking is sometimes too short for WTMM to detect. For example, one rides a bicycle to the parking area close to a bus station, then walks to the bus station to get onto a bus immediately (namely a bicycle-walk-bus trip). The walking segment between bicycle and bus is too short to generate clear singular points in wavelet transform. Another major error sources come from Bus-Walk transfer detection. TABLE 1 shows that the error of Bus-Walk transfer time detection is relatively significant, 21.2% of the detections result in an error of 120-180s. This is because some bus stops of those sample trips are placed very close to upstream intersections. Vehicles can have extended continuous stops both at intersections and bus stops, this phenomenon will lead to a relatively large error and misidentifications. However, the extremely short distance between bus stops and intersections is, in fact, a defect in the corresponding highway and
transit network design. Such error is expected to be eliminated when the design problems are fixed.

TABLE 1 Statistical Result of Traffic Mode Transfer Time Detection Error

<table>
<thead>
<tr>
<th>Transfer Patterns</th>
<th>Absolute Error Distribution (%)</th>
<th>Average Error (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0-60s</td>
<td>60-120s</td>
</tr>
<tr>
<td>Walk-Subway</td>
<td>90.0</td>
<td>7.0</td>
</tr>
<tr>
<td>Subway-Walk</td>
<td>90.0</td>
<td>5.0</td>
</tr>
<tr>
<td>Walk-Bus</td>
<td>81.2</td>
<td>11.9</td>
</tr>
<tr>
<td>Bus-Walk</td>
<td>63.5</td>
<td>10.6</td>
</tr>
<tr>
<td>Walk-Bicycle</td>
<td>92.0</td>
<td>3.3</td>
</tr>
<tr>
<td>Bicycle-Walk</td>
<td>77.8</td>
<td>4.0</td>
</tr>
<tr>
<td>Walk-Car</td>
<td>55.8</td>
<td>41.2</td>
</tr>
<tr>
<td>Car-Walk</td>
<td>74.5</td>
<td>15.6</td>
</tr>
</tbody>
</table>

Results of Trip Mode Detection

Table 2 shows the statistical results of mode detection accuracy. Results show that the accuracy of the mode detection results are over 86%. For walking and bicycle modes, the detection accuracy reaches 96.1% and 93.3%. This is due to the differences in velocity and acceleration fluctuations of walking and bicycle from those of the other travel modes. Bus and car mode achieve similar success rates of 88.8% and 86.0%. Mis-detections are observed for bus and car trip segments. They are related to the spacing issue between vehicle stops and its upstream intersections discussed above. In general, the proposed traffic mode detection model outperforms the existing GPS-based detection methods in detection accuracy. The reported bus mode detection accuracies are 76%(5), 53.3%(15), 82%(25), 81.8%(10) in different studies.

TABLE 2 Statistical Result of Trip Mode Detection Accuracy

<table>
<thead>
<tr>
<th>Modes</th>
<th>Identified as</th>
<th>Total trip segments</th>
<th>Correct segments</th>
<th>Success rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Walk</td>
<td>Bicycle</td>
<td>Bus</td>
<td>Car</td>
</tr>
<tr>
<td>Walk</td>
<td>1056</td>
<td>44</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bicycle</td>
<td>7</td>
<td>140</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Bus</td>
<td>11</td>
<td>5</td>
<td>311</td>
<td>23</td>
</tr>
<tr>
<td>Car</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>43</td>
</tr>
<tr>
<td>Total</td>
<td>1075</td>
<td>190</td>
<td>319</td>
<td>66</td>
</tr>
</tbody>
</table>

CONCLUSIONS AND FUTURE WORK

In this paper, a novel mode detection method is proposed and evaluated to detect trip modes under complex traffic environment by using GPS data and acceleration data. Compared with previous studies, the key contributions of the proposed model include the followings. First, different from using traditional handheld GPS devices, in this study, a cell phone sensor based mobile application is developed for passive multi-mode travel trajectory data collection. Field tests are designed and conducted in complex traffic environment areas. This study further explored the feasibility of improving trip mode detection accuracy by using GPS data combined with acceleration data from cell phones.
Second, most previous models use empirical travel time and distance thresholds for trip segment division which lacks universality and transferability under complex traffic environment. In this paper, a wavelet transform modulus maximum model is developed for trip segment division. Results show that the proposed method is efficient in the detection of mode transfer times. The average detection errors of all the mode transfer patterns are within one minute, and the ratio of unidentified or misidentified transfer points are less than 5%. Third, this paper comprehensively analyzed the characteristics of cell phone sensor data for different trip modes. A neural network based model is further established specifically for trip mode detection. Experiment results show that the method has an average mode detection accuracy of 93.9%.

This research can be further extended for travel behavior data collection in more complex urban areas such as central business districts (CBDs), where the canyon effect on GPS signal is significant. Meanwhile, further tests will be conducted to explore the influence of traffic congestion.

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