

Using Street-view Panoramas to Model the Decision-Making Complexity of Road Intersections Based on the Passing Branches during Navigation

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Highlights.

- Characterize road intersections via their visual, structural and semantic features
- Quantify the complexity of road intersections based on entry/exit branches
- Integrate complexity metric into route planning to generate least-complex route

Abstract.

The complexity of urban physical environments at road intersections is a primary factor characterizing the difficulty of wayfinding, which is a fundamental spatial activity of human beings in cities. A complex intersection may increase the difficulty of understanding the environment, which may result in incorrect turning decisions and even bring road safety issues. Existing methods measure the complexity of road intersections by solely considering their visual or structural features. More importantly, they only output a single complexity value for each intersection, failing to differentiate the decision-making complexity based on the specific entry/exit branches of a passing branches. This study proposes a computational model to quantify the fine-grained decision-making complexity of road intersections for the navigation data models and navigation systems based on specific passing branches, using the visual, structural, and semantic features from human perspectives. For each pair of two branches (i.e., one entry and one exit) passing through the road intersection, the model will output a specific decision-making complexity score. Furthermore, this study develops a route

planning algorithm for generating the minimum complexity route to serve relevant navigation applications. This study contributes to human-centered route planning and communication, as well as enabling potential innovative applications in traffic safety studies and sustainable urban and environmental development.

Keywords.

Urban Streetscape, Road Intersection, Decision-Making Complexity, Route Planning

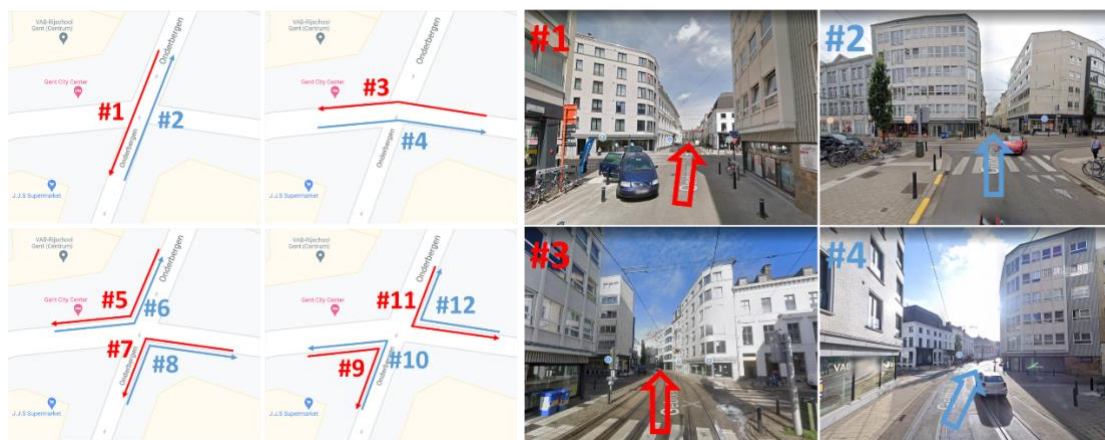
1 Introduction

Road intersections are critical areas during wayfinding (Daniel and Denis, 1998), which is one of the most common activities people encounter in urban environments. They are locations where route-following and wayfinding errors mainly occur (Richter, 2009; Zhou et al., 2019). Wayfinders must make turning decisions (e.g., left, right, or straight ahead) at these locations. The complexity of road intersections is one of the fundamental environmental characteristics affecting the performance and success of a wayfinding task. Specifically, it affects spatial cognition processes including interpretation, comprehension, memory and execution of turning decisions. At complex road intersections, people often have difficulty comprehending the street-view scenes and building a mental representation (Kim, 2001). As a result, wayfinders also tend to make more mistakes, need more time, and get frustrated at such environments, which sometimes may lead to navigation failure or brings road safety issues (Richter, 2009; Tapiro *et al.*, 2020). Modelling the decision-making complexity of road intersections (i.e., the complexity of making a correct turning decision at the intersections based on a specific entry and exit branches from a navigation perspective) has attracted significant research interests from various fields including urban planning, transportation, buildings and environments, and human behaviors. Such research potentially also enables many innovative applications, such as smart navigation systems (e.g., offering navigation routes avoiding complex intersections, providing route guidance adapting to the intersection complexity), smart transportation systems, road safety studies, and sustainable urban planning (Guan *et al.*, 2022; Rajagopal *et al.*, 2023).

Existing methods for quantitative computation of intersection complexity mainly involve two categories: one focusing on the structural characteristics of the road networks and the areas around intersections, and the other on the visual characteristics. The former typically extracts the structural features of road networks, such as the number of branches and spatial configuration of branches (Sladewski *et al.*, 2017; Zhou *et al.*, 2019). The latter extracts the visual features from the images of road intersections (Golledge 1999; Sanocki *et al.*, 2015), using pixel-level and/or region-level image features. Research combining visual and structural aspects, and beyond is rarely seen in the literature. However, research showed that both visual and structural salience have significant impacts on navigation cues (e.g., landmarks and salient buildings) for wayfinding (Winter *et al.*, 2005; Yesiltepe *et al.*, 2020). One exception is Guan *et al.* (2022), which combined features in the visual, structural, and semantic dimensions to

quantify the scene complexity of real-world street environments. However, this research, together with a vast majority of existing studies, exclusively treats each road intersection as a single entity: They assign each road intersection a unique complexity value, without considering the entry branch and existing branches when passing the road intersections.

In the literature, many empirical studies suggest that the following factors affect wayfinder’s perceived complexity for the wayfinding task, including personal experience and expertise, physical environments’ characteristics, and route features (Fang *et al.*, 2015; Giannopoulos *et al.*, 2014; Schmidt *et al.*, 1999). Indeed, the human perceived complexity of road intersections for making decisions depends not only on the structural configuration of road networks but also on the visual sensing of the real scenes, as well as the availability of semantic features (e.g., well-known points of interest (POIs)) in the environment (Guan *et al.*, 2022; Raubal and Winter, 2002; Sorrows and Hirtle, 1999). Additionally, different passing directions at a road intersection provide pedestrians with different perceptual information (‘environmental cues’). **Figure 1(a)** gives an example of a four-branch road intersection with twelve passing routes (i.e., twelve pairs of entry branch and exit branch) corresponding to twelve decision-making complexity results. **Figure 1(b)** displays examples of real-world street-view images from different viewpoints, revealing the significant differences in the visual information presented by the physical environment under different orientations and viewpoints. Therefore, it is reasonable to assume that different passing routes and directions at this road intersection will lead to different complexity of turning decisions. This phenomenon is in line with other empirical studies (Bongiorno *et al.*, 2021; Klippel and Winter, 2005; Perebner *et al.*, 2019; Richter, 2009), which show that different walking routes (i.e. different passing routes and directions of crossing intersections) correspond to varying complexity values. Therefore, the computation of a road intersection’s complexity needs to not only integrate the environmental features on the visual, structural, and semantic aspects, but also consider the specific pair of entry and exit branches when passing the road intersection. However, to our knowledge, computational methods addressing this issue are still missing in the literature.



(a) Possible paths of crossing.

(b) Street-views from different perspectives.

Figure 1. Example of a four-branch intersection with 12 possible paths of crossing (a). The street-view scenes of the first 4 paths (marked with #1-#4 in (a)) are shown in (b).

To fill these research gaps, this study proposes a computational method to quantify the decision-making complexity of road intersections (i.e., the complexity of making the correct turning decision or choosing the correct exit branch from all alternative branches) based on a specific pair of entry and exit branches, to enhance the navigation data model. Specifically, this study proposes six features to characterize the visual (i.e., visual similarity of the exit branch and its nearby branches, visual openness of the forward direction), structural (i.e., number of branches, relative angular deviation of adjacent branches), and semantic (i.e., well-knownness of the nearest POI, total well-knownness of POIs) aspects of the physical environment. These features can be extracted from open-access geodata (i.e., street-view panoramic images, road network data, and POIs data). They are computed for each pair of passing branches (i.e., the combination of an entry and an exit branch) and then are integrated to quantify the decision-making complexity. As a result, an n -branch intersection will correspond to multiple ($A_n^2 = n \times (n-1)$) refined results, respectively. In comparison with existing studies, the proposed method considers the specific passing route and direction of crossing a road intersection, and outputs multiple fine-grained results, which is more appropriate than existing methods which outputs only a single value for each road intersection. The contributions of this study are as follows:

- (1) To the best of our knowledge, this study is the first to quantify the decision-making complexity of road intersections according to a specific pair of entry /exit branches during navigation. It therefore fills a research gap of fine-grained complexity quantification of road intersections for different passing routes.
- (2) This study comprehensively characterizes the physical environments of road intersections from navigation perspectives. Specifically, six environmental features in visual, structural, and semantic dimensions are extracted from street-view panoramic images and open geo-datasets. The six features are integrated to compute the decision-making complexity of road intersections.
- (3) This study further applies the decision-making complexity to navigation applications, and develops a route planning algorithm for generating a route with minimum decision-making complexity. The comparisons between generated the minimum complexity routes (MCRs) with the shortest routes (SRs) and the fewest turns routes (FTRs) demonstrate that the proposed algorithm can minimize the decision-making complexity while maintaining a low walking detour.

2 Related works

2.1 Studies of Road and Environment Complexity

Current research on road complexity mainly involves the structural complexity of geographical and physical environments (or spatial configuration) and the visual

complexity of real-world scenes. The former focused on quantifying the local or global structural characteristics of road segments and intersections to physically represent the spatial and structural complexity of road networks. For example, some studies investigated the complexity of road networks based on identified influential factors, such as the number of nodes (O'Neill 1991; Mark, 1986), branches (Richter, 2009; Zhou *et al.*, 2019), and turns (Golledge *et al.*, 1995), as well as the direction deviation between adjacent route segments (Conroy *et al.*, 2001). Furthermore, some studies focus on measuring the complexity of individual road intersections, using the number of branches and their spatial configuration, the ambiguity of turning instructions at the intersection, the length of route segment, and the shape of the branches (Krisp and Keler, 2015; Richter, 2009; Zhou *et al.*, 2019). For example, executing the instruction 'turn left' becomes more complex when there are several alternatives on the left side compared to when there is only one branch heading in that left direction (Haque *et al.*, 2007). In addition, some well-known POIs may help to reduce cognitive difficulty and ambiguity, thereby decreasing decision complexity. References to salient geographic objects (e.g., 'turn left at the post office') anchor actions in space (Denis, 1997). These signals serve as critical references for performing navigation tasks, supporting navigation communications, and helping to identify the right spot for making the turning decisions (Lovelace *et al.*, 1999). Furthermore, space syntax (Hiller and Hanson 1984, Hiller and Penn 2004) was employed to analyze the road network attributes like choices, integration and depth distance for further quantifying the road complexity structurally, especially in indoor navigation systems (De Cock *et al.*, 2021; Zhou *et al.*, 2021). In addition to research focusing on the structural complexity, several studies have focused on the visual complexity of the environments. These studies extracted basic image features (e.g., color, shape, texture factor) to measure the visual complexity of scenes, and computed indexes of greenery (Green View Index, GVI), openness (Sky View Factor, SVF), enclosure, and blueness to represent the physical environments, and correlated these features with wayfinding behaviors (Golledge, 1999; Sanocki *et al.*, 2015; Larkin *et al.*, 2021).

Several empirical studies have revealed that the perceptual complexity is jointly characterized by the road environment, road geometry, traffic volume, the number of visual objects (with their shape, location, and content), and points of interest (Decker *et al.*, 2015; Oviedo-Trespalacios *et al.*, 2019; Tapiro *et al.*, 2020). However, current computational methods rarely comprehensively integrated structural, visual, or even semantic aspects of the road intersections when measuring decision-making complexity of road intersections, resulting in a mismatch between the computational results and the actual perceived complexity during navigation. Meanwhile, existing studies exclusively take a road intersection as a whole and fails to quantify fine-grained decision-making complexity according to a specific pair of entry and exit branches when passing the intersection.

2.2 Studies of Street-View Imagery

Street-view imagery serves as a new source of geographic information data and provides a realistic simulation of real-world scenes that has densely covered the road

networks of numerous cities worldwide (Zhang *et al.*, 2019, 2018; Zhou *et al.*, 2019). They work as an effective data source for urban street environments representation and street-level attributes analysis, including urban greenery analysis (Li *et al.*, 2018; Lauko *et al.*, 2020), urban landscape and neighborhood environment assessment (Helbich *et al.*, 2021; He and Li, 2021), urban public health analysis, e.g. health behavior and well-being (Kang *et al.*, 2020; Rzotkiewicz *et al.*, 2018), spatio-temporal visibility assessment (Kou *et al.* 2021), and walkability analysis (Yin, 2016), as well as the perceived scene complexity evaluation (Guan *et al.*, 2022). Additionally, street-view images are employed for social sensing and social economic and cultural analysis, including public transportation and human mobility analysis (Chen *et al.*, 2020), socio-economic (Biljecki and Ito, 2021), and real estate studies (Johnson *et al.*, 2019). In the field of navigation, scholars employed street-view images for positioning (Agarwal *et al.*, 2015; Salarian *et al.*, 2015) and route planning services (Runge *et al.*, 2016). However, existing street-view-based research rarely involves physical environments and road complexity evaluation.

2.3 Studies of Route Planning

Wayfinding research has inspired several algorithms that compute the shortest, fastest, or even most straightforward paths between two locations (Haque *et al.*, 2007). Many of them employed the classic Dijkstra algorithm and A* algorithm and provided users with the shortest or fastest path from an origin to destination. In recent years, methods of computing routes with other characteristics have also been proposed, such as fewest turns and minimal angle route (Winter, 2002; Jiang and Liu, 2011), least instruction complexity route (Duckham and Kulik, 2003), dedicated routes with minimum complex intersections and turns ambiguities (Haque *et al.*, 2007), and the most “pleasant” route (Huang *et al.*, 2014). However, current route planner and navigation systems do not consider the navigation complexity of certain road intersections. For example, a short route may involve several difficult-to-navigate intersections (e.g., intersections with similar or confusing turning alternatives) requiring lots of cognitive effort. People often need to spend more time and effort to make the correct navigation decisions at such intersections, which might lead to navigation failure or brings road safety issues.

3 Methodology

3.1 Overview

This study aims to quantify the decision-making complexity of road intersections for enhancing the navigation data model (i.e., the complexity of making a correct turning decision at the intersections) based on a pair of specific entry and exit branches. The visual, structural, and semantic features of physical environments are integrated for characterizing the physical environments. This research problem can be formulated as follows.

Research problem definition. Decision-making complexity of road intersections.

Given a pair of entry branch (en) and exit branch (ex) of crossing a road intersection $\{en, ex\} \in \{branch_1, branch_2, \dots, branch_n\}$, which is characterized by a vector of its environment features in the visual, structural, semantic dimensions $f_{intersection} = \{f_{vis} \dots, f_{str} \dots, f_{sem}\}$, return the decision-making complexity of crossing the intersection via this passing route $\{en, ex\}$ as a continuous value from 0 to 1.

This study develops a framework that integrates a variety of geographic data sources and extracts a series of visual, structural, and semantic features of the physical environments, to quantify the decision-making complexity of road intersections for the navigation data models and navigation systems. The following open data sources are used in this study, including urban street-view panoramic images, urban road networks, and POIs data. These data are widely available from map service providers in many countries and regions. **Figure 2** illustrates the methodological framework consisting of the data sources module, and road intersection features characterization, calculation constraint, and integrated computation module. **Table 1** lists the proposed complexity features for characterizing the physical environments of road intersections.

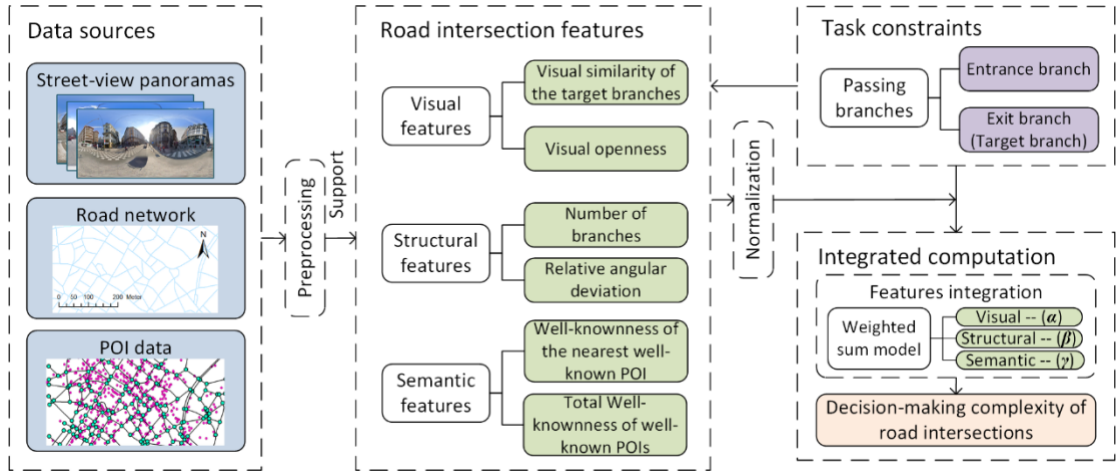


Figure 2. The proposed methodological framework.

Table 1. Complexity features of road intersections.

Dimension	Scene feature descriptions
Visual features	<i>Visual similarity of the target branch and its adjacent branches</i> (<i>vis_branch_similarity</i>)
	<i>Visual openness of the target branch</i> (<i>vis_openness</i>)
Structural features	<i>Number of branches</i> (<i>str_branch_number</i>)
	<i>Relative angular deviation of adjacent branches</i> (<i>str_branch_rangular</i>)
Semantic features	<i>Well-knownness of the nearest well-known POI</i> (<i>sem_nearestPOI_wkn</i>)
	<i>Total well-knownness of well-known POIs</i> (<i>sem_totalPOIs_wkn</i>)

3.2 Visual Features of Road Intersections

3.2.1 Conceptualization of the Proposed Visual Features

The **visual features** describe the overall and partial visual impressions of the intersection environment. Research on cognitive science shows that humans acquire

external information primarily through vision (Kalat, 2015), which is the main driver behind human perception (Brakus *et al.*, 2009). For example, the isovist has been widely employed to quantify visual exposure. Isovist analysis can be done on 2D or 3D spatial data. However, 2D spatial data lack detailed descriptions of the environment, such as occlusion information caused by urban trees and buildings. 3D models of urban environments can be used to overcome this issue, but they are often unavailable and difficult to obtain. Street-view panoramic images are a good proxy for real-world scenarios, supporting many relevant studies on urban environments (Zhou *et al.*, 2019). Consequently, this study chooses urban street-view panoramic images and road networks as alternatives to 3D models. Then, this study represents the visual characteristics of a pair of passing branches of the road intersection through the following two features.

Visual similarity of the target branch and its adjacent branches (*vis_branch_similarity*) refers to the visual similarity of the environmental scene of the target branch (i.e., the exit branch) versus those of its adjacent branches. This feature aims to quantify the complexity of selecting the correct branch as an exit from all alternative branches at the road intersection. It might be a significant challenge for a wayfinder if the target branch is visually similar to an adjacent one.

Visual openness of the target branch (*vis_openness*) refers to the visual openness of the field of vision in the forward direction (i.e., from the entry branch to the target/exit branch) as viewed from a human perspective at street level. It is measured via the area of building facades and that of the visible sky (Shach-Pinsly *et al.*, 2011).

3.2.2 Computational Methods of the Visual Features

The pre-processing steps of street-view panoramic images and the computation method of visual features are introduced below (see **Figure 3** and **Figure 4**).

Pre-processing of street-view panoramic images.

- Step 1:** Selecting all the street-view panoramic images closest to the road intersections in the study area.
- Step 2:** Re-projecting the street-view panoramic images to Equal-Area Projection, which prevents area distortion of the images.
- Step 3:** Segmenting the re-projected street-view panoramic images through a pre-trained RefineNet model. It is a semantic segmentation model trained through the Cityscape dataset and can extract accurate semantic information for several pixel sets (Lin *et al.*, 2018; Regmi *et al.*, 2018).
- Step 4:** Taking the moving objects (e.g., vehicles, bicycles, pedestrians) as a background set and retaining static environmental objects (e.g., sky, building, and road) as target sets from segmented panoramas.
- Step 5:** Generating a masked building layer (*mask_layer*) by fusing the masked building areas (*segbld_pano*) split in Step 4 with the original street-view panoramic images (*ori_pano*), as in **Eq. (1)**.

$$mask_layer(seg_pano(x, y), ori_pano(x, y)) = seg_pano(x, y) \cap ori_pano(x, y) \quad (1)$$

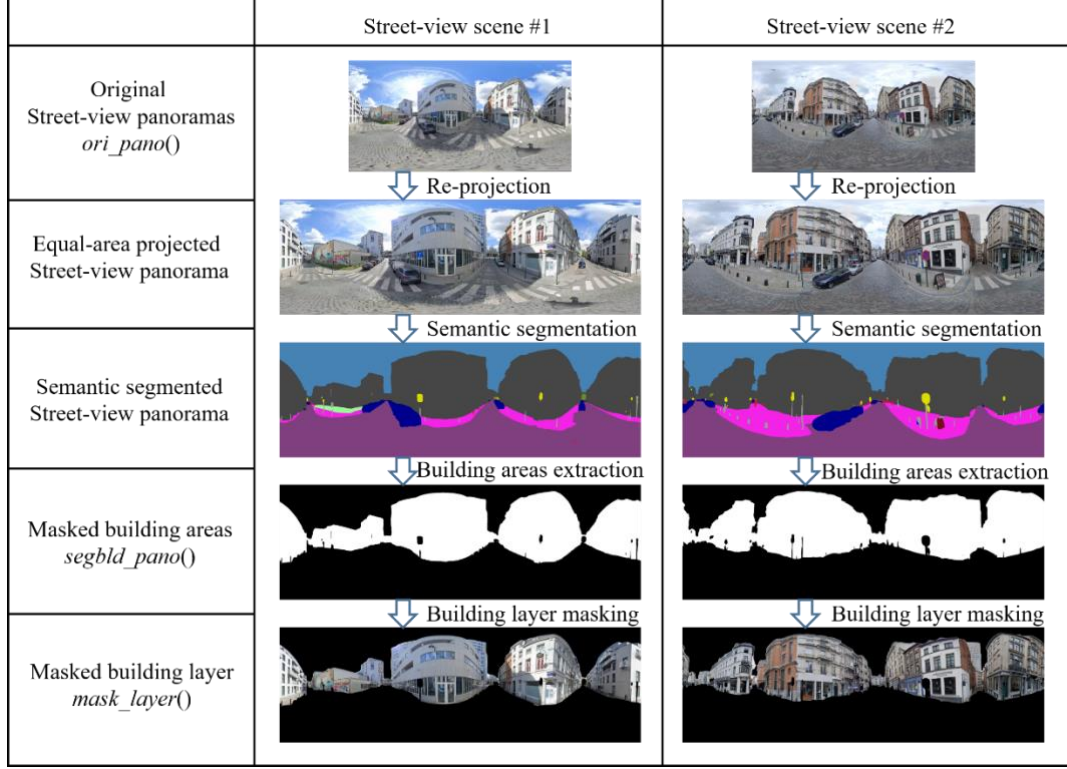


Figure 3. Pre-processing of street-view panoramic images.

Computation of the feature “Visual similarity of the target branch and its adjacent branches (*vis_branch_similarity*)”. This study first extracts the segmented slices of street-view panoramic images of the target branch and its adjacent branches, and employs the Perceptual Hash Algorithm (PHA) to quantify the visual similarity between these segmented slices. **Figure 4** presents the computation processes.

Step 1: Segmenting the street-view panoramic images from *mask_layer()* into n -slices based on directions of the intersection’s branches and computing its relative angular range (*RelativeAngular_range*) as *Eq.(2)* and *Eq.(3)*, where n is the number of branches.

Step 2: Computing the visual similarity metric based on PHA as follows.

- (1) Resizing the slices into $8*8$ pixels, and sampling the color feature into 64-scale.
- (2) Employing the Discrete Cosine Transform (DCT) to obtain a $32*32$ DCT coefficient matrix, and resizing the DCT to keep only the $8*8$ matrix in the lowest frequency part of the upper left corner.
- (3) Comparing the grayscale value of each pixel (g_{pixel}) with the mean grayscale value ($\overline{g_{pixel}}$), and mapping the results into (0, 1) as basic hash values as *Eq.(4)*.
- (4) Organizing the hash values as a fingerprint of the slice as *Eq.(5)*.
- (5) Comparing the visual similarity of adjacent branches’ slices by computing the Hamming distance of slices’ fingerprints. Finally, outputting the probability of visual similarity of adjacent branches’ slices as *Eq.(6)*.

$$RelativeAngular_range(RA_{ex}) = \left(\frac{RA_{ex-1} + RA_{ex}}{2}, \frac{RA_{ex} + RA_{ex+1}}{2} \right) \quad (2)$$

$$pixel_range(x_{ex-1}, x_{ex}) = \begin{cases} \left(\frac{RA_{ex-1}}{360} \times Img_width, \frac{RA_{ex}}{360} \times Img_width \right), & (RA_{ex-1} < RA_{ex-1}) \\ \left(\frac{RA_{ex-1}}{360} \times Img_width, Img_width \right) \text{and} \left(0, \frac{RA_{ex}}{360} \right), & (RA_{ex-1} > RA_{ex-1}) \end{cases} \quad (3)$$

$$pHash_i(pixel_i, \overline{pixel}) = \begin{cases} (1, IF \ g_pixel_i \geq \overline{pixel}) \\ (0, IF \ g_pixel_i < \overline{pixel}) \end{cases} \quad (4)$$

$$fingerprint_slice_j(hash_value_n) = (hash_value_0, hash_value_1, \dots, hash_value_{63}) \quad (5)$$

$$vis_branch_similarity(slice_j, slice_{j+1}) = \frac{\sum(fingerprint_slice_j[k] \oplus fingerprint_slice_{j+1}[k])/64}{\sum(fingerprint_slice_j[k] \oplus fingerprint_slice_{j+1}[k])/64} \quad (6)$$

where \oplus is the logical operation “exclusive or” (XOR), which is true if and only if its arguments different.

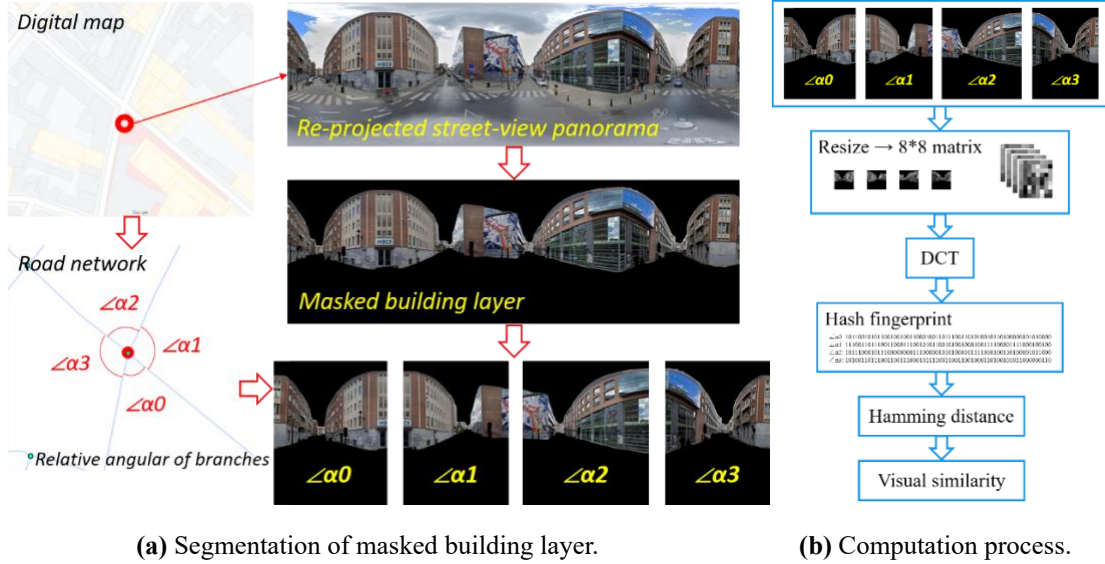


Figure 4. Computation processes of the visual features ($vis_branch_similarity$).

Computation of the feature “Visual openness (i.e., the field of vision) of the target branch ($vis_openness$)”. To compute this feature, this research first extracts the 124° range area (the horizontal Field of View (FOV) of a steady gaze from both human eyes is considered to be 124° (Tara *et al.*, 2021)) of street-view panoramic images in the target branch’s direction, and consider this extracted part as the field of view when looking at the target branch. This research then computes the areal ratio of buildings and sky in this extracted part.

Step 1: Splitting a 124° visible range of semantic segmented panoramas in the forward direction of the target branch and computing the areas of the sky and buildings.

Step 2: Computing the visual openness of the branch as Eq.(7).

$$vis_openness(B_{ex}) = \frac{\sum area_building}{\sum area_sky} \quad (7)$$

3.3 Structural Features of Road Intersections

3.3.1 Conceptualization of the Proposed Structural Features

The **structural features** of the road network spatially describe the fundamental geometric properties of the physical navigation environments, which also influence pedestrians' turning decisions during navigation. Current studies demonstrate that these geometric features, including geometry-related features, distance-related features, and sequence of segments, as well as the intersection characteristics and their configurations, are the principal factors contributing to environments' complexity and decision-making difficulty (Giannopoulos *et al.*, 2014). In general, more branches will result in higher complexity for decision-making. Additionally, the structural properties of road intersection branches, in particular the feature of relative angular deviation of the target branch from the adjacent branches, influence the complexity of wayfinding. Accordingly, this study considers the following structural characteristics of the road network with respect to the passing branches.

Number of branches (*str_branch_number*) refers to the number of branches of an intersection, often used as a criterion for complexity measurement (Richter, 2009; Zhou *et al.*, 2019), and also affects the difficulty of that path selection. Typically, more branches lead to a higher complexity for making turning decisions at this intersection.

Relative angular deviation of adjacent branches (*str_branch_rangular*) quantifies the spatial angular proximity of a target branch to its neighbouring branches. A pair of adjacent branches with small angular differences from the target branch is challenging to distinguish spatially. In particular, intersections that offer multiple turns (including the target turn) in the same conceptual direction are more complex (Richter, 2009).

3.3.2 Computational Method of Structural Features

Pre-processing of the road network. This research reduces the effects of noisy road segments (e.g., multi-cover roads) by detecting and deleting subsidies roads (e.g., multi-way roads, bridge, tunnel, smaller local roads, cycle-way, foot-way, steps) based on the OSM document (Frederik Ramm, OpenStreetMap Data in Layered GIS Format, version 0.7.11).

Computation of the feature “Number of branches (*str_branch_number*)”. This study detects the nodes on the road network and calculates the number of route segments that intersect the nodes as the number of branches.

Computation of the feature “Relative angular deviation of adjacent branches (*str_branch_rangular*)”. The relative angular (Δang_i) deviation between the target branch and its adjacent branches is used for quantifying the spatial angular proximity. In case of the exit branch is adjacent to the entry (i.e., the intersection only has three branches), only another neighboring branch of the target exit needs to be considered, as shown in *Eq.(8)*. Otherwise, both neighboring branches are required as *Eq.(9)*.

$$str_branch_rangular(en, ex) = \cos(\Delta ang_{ex \rightarrow ex+1}) \quad (8)$$

$$str_branch_rangular(en, ex) = \cos(\Delta ang_{ex \rightarrow ex-1}) + \cos(\Delta ang_{ex \rightarrow ex+1}) \quad (9)$$

Where $\Delta ang_{ex \rightarrow ex-1}$ & $\Delta ang_{ex \rightarrow ex+1} \in (0, 180)$.

3.4 Semantic Features of Road Intersections

3.4.1 Conceptualization of the Proposed Semantic Features

The **semantic features** describe the semantic saliency and potential social-cultural attributes of a real-world street environment. Such features can be extracted in various ways, either through intuitive visual information (e.g., sign or billboard of a well-known brand/shop) or indirectly through other data sources (e.g., geographic information data or social media data). For example, POIs are geospatial objects that carry semantic information in the environment and play an important role in navigation and spatial cognition tasks (Duckham *et al.*, 2010; Quesnot and Roche, 2015). In particular, those well-known POIs with prominent historical, economic-social, and cultural features, such as famous and influential commercial brands, companies, stores, restaurants, social organizations, and institutions, are more likely to attract people's attention and effectively contribute to the perception and understanding of the streetscape environment. Well-known POIs located around a road intersection provide semantic "navigation cues" for pedestrians to relieve the stress of cognition and navigation caused by complex environments, especially for decision-making at road. Such POIs are also often included intersections in navigation systems, e.g., embedded in verbal instructions or visualized in a navigation map, to provide more effective navigation guidance (Huang *et al.*, 2018). Consequently, the following semantic features are designed to capture the semantic characteristics of the target branch, using POIs and their reviews and check-in data.

Well-knownness of the nearest well-known POI (*sem_nearestPOI_wkn*) refers to the popularity attribute of the nearest well-known POI to the target road intersection, which quantifies the local semantic impact of the nearest well-known POI.

Total Well-knownness of well-known POIs (*sem_totalPOIs_wkn*) refers to the global popularity properties of the target branch of the intersection.

3.4.2 Computational Method of Semantic Features

To compute the above semantic features, this study incorporates the check-in data and review data of POIs, which can reflect the popularity of POIs and support for mining potential semantic features (Cao *et al.*, 2014; Scellato and Mascolo, 2011). The calculation processes are as follows.

To pre-process the original POIs data, this research screens for well-known ones by sorting the POIs based on their total users' reviews, and define those POIs ranked in the top 30% of the total number of reviews as well-known POIs. Then the semantic features of the **well-knownness of POI** are calculated as follows.

Step 1: Generating a buffer at a road intersection and then dividing the branches it connects. If the target exit branch length is shorter than the buffer radius, the branch will not be segmented. Note that the analysis is facilitated by employing a single buffer, as the inclusion of multiple buffers for a study area may lead to multicollinearity (Browning and Lee, 2017; Nordbø *et al.*, 2018). Existing literature does not provide empirical insights regarding the effective visual distance for a person in an urban area. By checking the visibility of street signs and objects in Brussels and based on common sense, we set that

effective visual distance as 50 meters. In other words, the buffer was set to 50 meters for this study.

Step 2: Selecting the well-known POIs from the divided segment (i.e. the connected part with the target intersection) and computing the distances between the well-known POIs to the target intersection.

Step 3: Computing the *well-knownness* of the nearest POI and the *total well-knownness of POIs* of the target exit branch by integrating their distance factors as *Eq.(10)* and *Eq.(11)*.

$$sem_nearestPOI_wkn(POI, dis_POI) = \frac{distance_POI_i}{\log_{10}(\#reviews_POI_i)} \quad (10)$$

$$sem_totalPOIs_wkn(POIs, dis_POIs) = \sum \frac{distance_POI_i}{\log_{10}(\#reviews_POI_i)} \quad (11)$$

3.5 Integration of all proposed features to measure the decision-making complexity of an intersection

The above sections propose a series of visual, structural, and semantic features to capture the characteristics of the area around a specific road intersection. In this section, this study combines all these features to quantify the decision-making complexity of a specific pair of entry and exit branches at an intersection as *Eq.(12)* and *Eq.(13)*.

Inspired by Raubal and Winter (2002), a well-cited study on combining visual, structural, and semantic features, and many other related studies (e.g., Nuhn (2019)), this study employs a weighted sum model that assigns different weights to the three dimensions. Each feature is normalized to the interval [0,1] using Min-Max feature scaling.

$$\begin{cases} Cpx(en, ex) = w_\alpha \times f_{str} + w_\beta \times f_{vis} + w_\gamma \times f_{sem} \\ w_\alpha + w_\beta + w_\gamma = 1 \end{cases} \quad (12)$$

$$\begin{cases} f_{str} = str_branch_number(en, ex) + str_branch_rangular(en, ex) \\ f_{vis} = vis_branch_similarity(en, ex) + vis_openness(en, ex) \\ f_{sem} = sem_nearestPOI_wkn(en, ex) + sem_totalPOIs_wkn(en, ex) \end{cases} \quad (13)$$

Existing research suggests that structural features of a road intersection have significant effects on self-localization, orientation, and wayfinding (Zhou *et al.*, 2019; Nuhn, 2019). As a result, this research assigns a higher weight to the structural dimension, setting w_α as 0.5 and w_β and w_γ as 0.25.

3.6 Route planning that considers the decision-making complexity of an intersection

The decision-making complexity of intersections can be integrated into route planning services, such as generating a low-complexity route that avoids complex intersections for people in unfamiliar environments, or generating a high-complexity route for driving training and testing (e.g., for human drivers). This section integrates the proposed decision-making complexity of road intersections into a route planning service for generating a low-complexity route while maintaining a reasonable walking distance.

Similar to Huang et al. (2014), in order to generate routes considering intersection complexity while maintaining a reasonable path length, a top-k shortest path algorithm, e.g., Yen’s algorithm (Yen 1971), is used to find all the routes that are not longer than $(1 + \delta) \times Dist_{shortest}$, where $Dist_{shortest}$ is the shortest distance between the origin and the destination (i.e., the length of the shortest path). The route with the minimum total complexity value is then returned as the result. The detour threshold δ reflects how much longer a user is willing to take for a less complexity route instead of the shortest one. It can be provided by the users themselves when asking for a route or automatically learned from their travel histories. Similar to Huang et al. (2014), in the evaluation (Section 4), this study sets the detour threshold δ as 10%. In other words, this research considers only routes that are shorter than 110% of the shortest distance.

Figure 5 illustrates the route planning algorithm. Note that the computation of decision-making complexity (Sections 3.1-3.5) can be done in advance, before running the route planning algorithm. The time complexity of the route planning algorithm then mainly originates from the top-k shortest path algorithm, which is actually not much higher than a simple shortest-path calculation since it is just a repetition of the latter within a loop until a detour threshold is reached (Huang *et al.*, 2022). Meanwhile, currently, the algorithm performs an additional scan to identify the route with the minimum total complexity value. However, it is possible to combine this scan together with Yen’s top-K algorithm for better performance.

This routing algorithm differs from conventional approaches, which often combine distance and other route characteristics using different weights to generate an overall cost. It is challenging to set the optimal importance weights of distance and other route characteristics in these traditional methods. As a result, this study utilizes the detour concept (δ), which is more intuitive and easier to configure by the user who requests a route.

Algorithm: Minimum total Complexity Route (MCR)

Input: *Directed_network* G : the road network with necessary data fields for shortest route search; complexity dataset D , containing the complexity values of each pair of branches at each road intersection (computed using the method proposed in Section 3.5); s_node : the start node ID in the *Directed_network*; e_node : the end node ID in the *Directed_network*; detour threshold δ .

Output: The minimum total complexity route (MCR).

```
//compute the shortest distance between  $s\_node$  and  $e\_ndoe$  by using Dijkstra algorithm
Distshortest = Get_shortest_distance( $G, s\_node, e\_ndoe$ );

//find all the routes that are shorter than  $(100\% + \delta) * Dist_{shortest}$ , using Yen's top-K shortest route
algorithm
Candidate_Routes = Yen_TopK( $G, s\_node, e\_ndoe, (100\% + \delta) * Dist_{shortest}$ );

//Identify the route with the minimum total complexity values
Min_Complexity_value = 0;
Min_Complexity_route = null;
FOR each route  $r$  in Candidate_Routes DO
    Total_Complexity_value = 0;
    FOR each route segment  $en$  in route  $r$  DO
        IF ( $en$  is the last route segment in  $r$ ) THEN
            Break;
        ENDIF
         $ex = Get\_Next\_RouteSegment(r, en)$ ; //get the next road segment after  $en$ 
        //get the complexity value based on the entry ( $en$ ) and the exit ( $ex$ ) branches, using the
        //proposed method in Section 3.5.
        Complexity = Get_Complexity( $en, ex$ );
        Total_Complexity_value = Total_Complexity_value + Complexity;
    ENDFOR
    IF (Total_Complexity_value < Min_Complexity_value) THEN
        Min_Complexity_value = Total_Complexity_value;
        Min_Complexity_route =  $r$ 
    ENDIF
ENDFOR

RETURN Min_Complexity_route;
```

Figure 5. The complexity-based route planning algorithm.

4 Case Study and Results

4.1 Study Area and Data Sources

Brussels, the capital of Belgium, is one of the largest cities in Europe, with

complex urban built environments and road network. This work selected the Brussels city centre as the study area. Data of Brussels's road network, Google-Street-View (GSV) panoramas and point of interest (POI) were requested and downloaded from the map service providers. Then, a total of 350 road intersections were extracted from the road network in the study area. ArcMap was used as the GIS platform to process and integrate the geo-data. **Figure 6** displays the study area and the data for the case study. The experimental data were requested and collected as follows.

- (1) GSV panoramas were requested and downloaded from Google Maps Platform (API: <https://maps.googleapis.com/maps/api/streetview/>).
- (2) Road network data were downloaded from OpenStreetMap database (<https://www.openstreetmap.org>).
- (3) POIs and their users' reviews data were downloaded from Google Maps Platform (API: <https://maps.googleapis.com/maps/api/place/details/>).

Note that these data can be requested and acquired via map services such as Google Maps Platform and OpenStreetMap, making it possible to apply the proposed method to other cities worldwide.

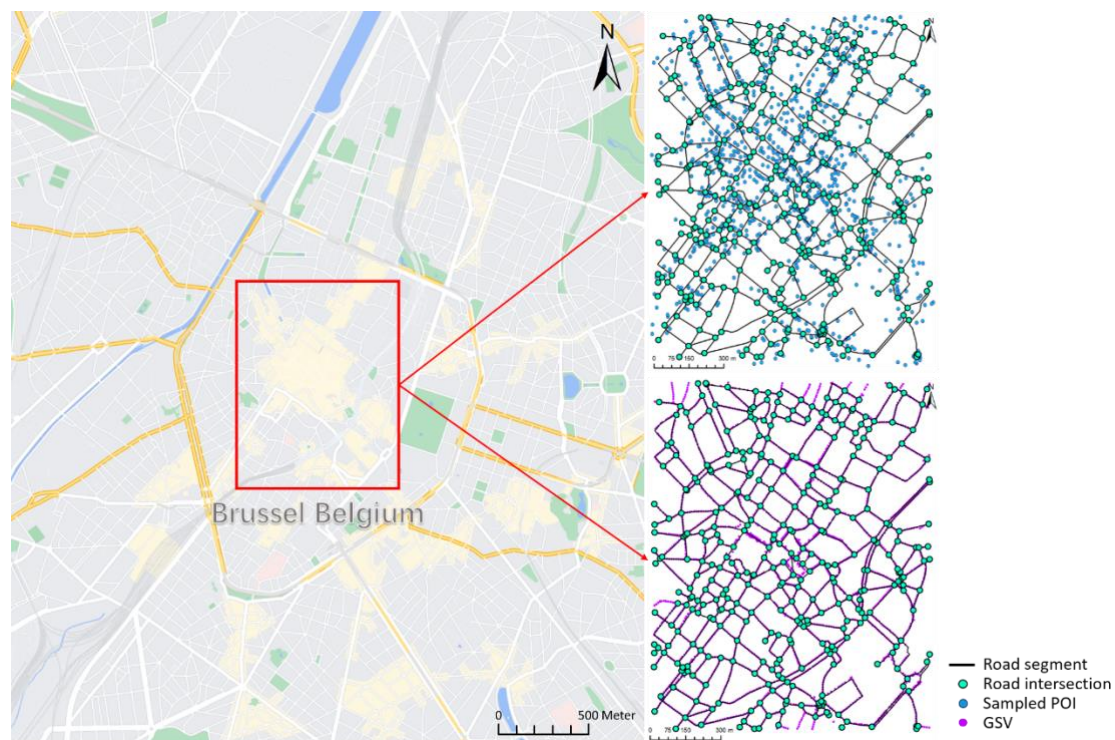


Figure 6. Study area and experimental data.

4.2 Results of Road Intersections' Complexity

4.2.1 Comparisons of Decision-Making Complexity of Typical Road Intersections

Figure 7 shows eight street-view images taken at different viewpoints at five road intersections, where the complexity of each pair of branches is displayed. The following observations can be documented by analyzing the computed complexity of different pairs of branches.

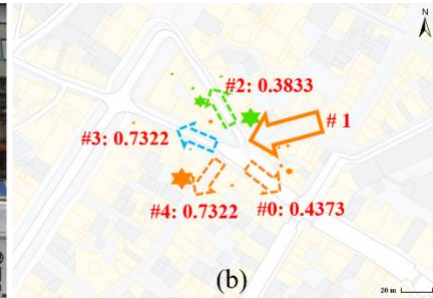
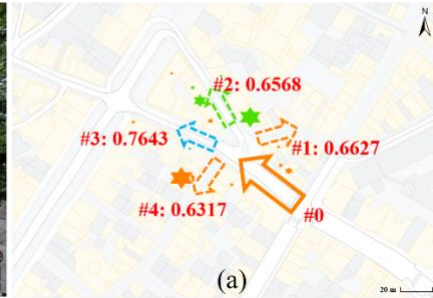
- (1) At the same intersection, depending on the pair of entry and exit branches, the complexity of crossing this intersection varies greatly. This is desirable, as different navigation experiences can be expected according to the entry and

exit branches humans cross the intersection.

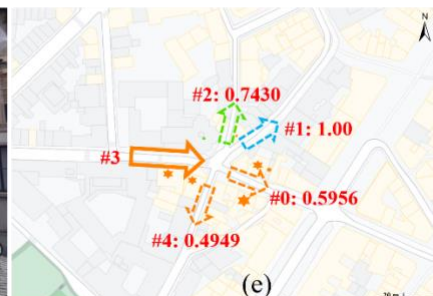
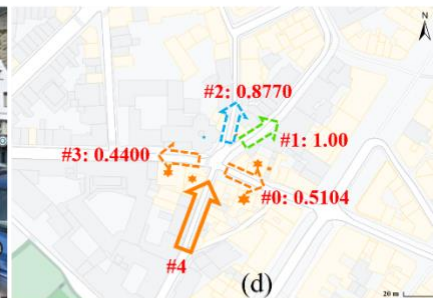
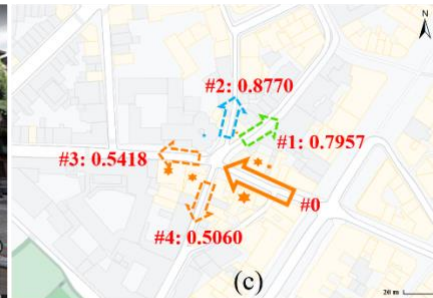
- (2) Road intersections with more branches (e.g., road intersections #A and #B in **Figure 7(a)**, **Figure 7(b)**, **Figure 7(c)**, **Figure 7(d)**, and **Figure 7(e)**) tend to have higher complexity values than road intersections with fewer branches (e.g., road intersections #C, #D, and #E in **Figure 7(f)**, **Figure 7(g)** and **Figure 7(h)**), in dependence of the pair of entry and exit branches. This is in line with the underlying assumption of the proposed complexity metric and findings of many existing studies, which highlight that the structural characteristics of road intersections significantly impact the complexity of making decisions, particularly the number of branches (Krisp and Keler, 2015; Richter, 2009; Zhou *et al.*, 2019).
- (3) At a road intersection, exit branches with similar angular bearing as their adjacent branches often have higher complexity values, e.g., branches #1 and #2 in **Figure 7(c)**, and branch #3 in **Figure 7(a)**. Such similar angular bearings might lead to the same conceptual directions (Conroy *et al.*, 2001; Richter, 2009). For example, branches #1 and #2 in **Figure 7(a)**, branches #2 and #3 in **Figure 7(b)**, and branches #1 and #2 in **Figure 7(c)** can be both conceptualized as “turning right”, and therefore, both branches have relatively higher complexity values than the other exit branches at this intersection.
- (4) Well-known POIs located at a branch help to reduce the complexity value of this branch. For example, branches #2 and #3 in **Figure 7(a)** have similar visual and structural characteristics. However, there are several well-known POIs (marked with green stars) located in branch #2, while branch #3 does not have any. Therefore, branch #3 has a much higher complexity value than that branch #2 (0.7643 vs. 0.6568). Similar effects can be observed in **Figure 7(b)**, **Figure 7(d)**, and **Figure 7(e)**.
- (5) A branch with a similar visual appearance as its adjacent branches increases the complexity value of this branch. For example, branches #3 and #4 in **Figure 7(b)** have very similar visual appearance when approaching branch #1, and therefore, both branches #3 and #4 have relatively higher complexity values than the other branches at this intersection.

As a proof-of-concept, the above observations are desirable, as they match the findings of many existing studies on the complexity of real-world urban environments as well as their impact on human navigation. They are also consistent with the underlying assumption of the proposed complexity modelling approach.

Example ①-② of Road Intersection #A



Example ③-⑤ of Road Intersection #B



Example ⑥-⑧ of Road Intersections #C-#E

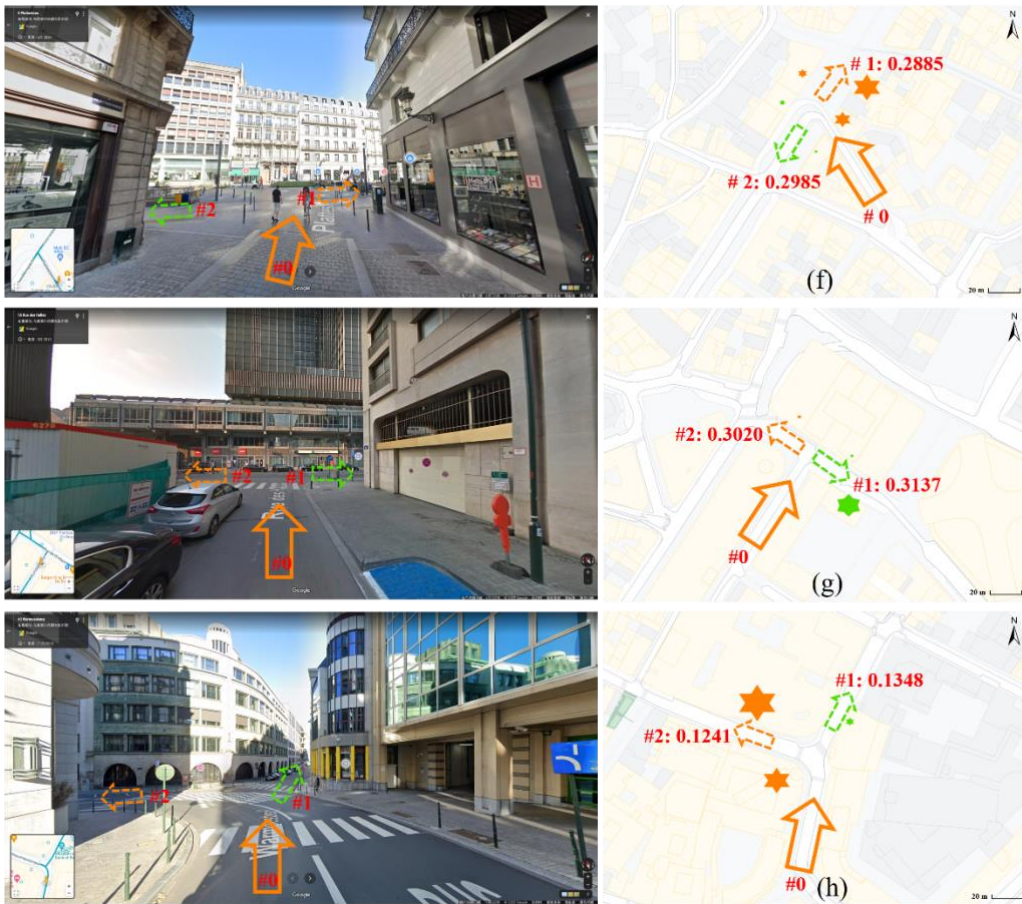


Figure 7. Examples of five road intersections with several viewpoints, where the values in red refer to the corresponding complexity results. Well-known POIs located on a branch are visualized as stars, whose size is proportionally to the number of reviews on that POI.

4.2.2 Analysis of Decision-Making Complexity of the whole study area

Figure 8 visualizes the top-20 pairs of entry/exit branches with the highest and the lowest decision-making complexity in the study area. As expected, the passing branches with high decision-making complexity are clustered in road intersections with more branches, which suggests that the structural characteristics of road intersections have a significant influence on the complexity of making the turning decision, confirming the findings of existing studies (Krisp and Keler, 2015; Richter, 2009; Zhou *et al.*, 2019). In contrast, those passing branches with the lowest decision-making complexity are usually centralized on those intersections with fewer branches. Additionally, many roadways with high decision-making complexity are not exclusively concentrated in downtown areas. This phenomenon is potentially attributed to the higher density of points of interest in the downtown area, which provides more semantic guidance cues, contributing to the decreased decision complexity of the downtown intersections.

Figure 9 statistically presents the complexity results for all road intersections within the study area and visualizes the distribution of results.

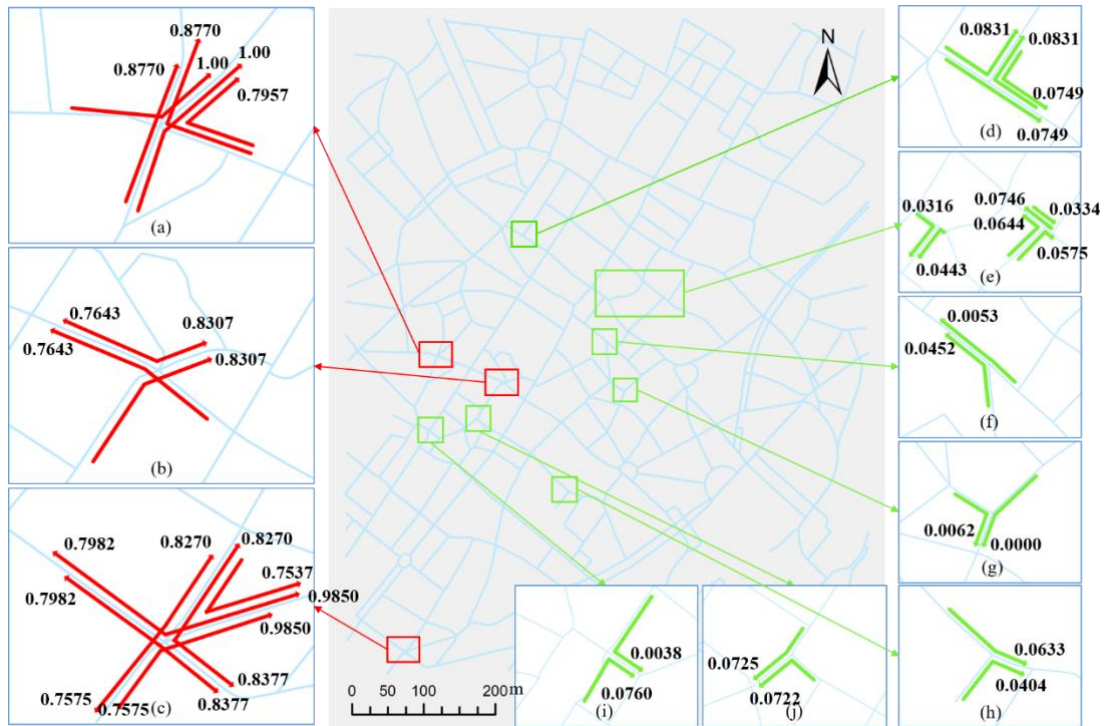


Figure 8. The top-20 highest (red) and the top-20 lowest (green) complexity passing branches.

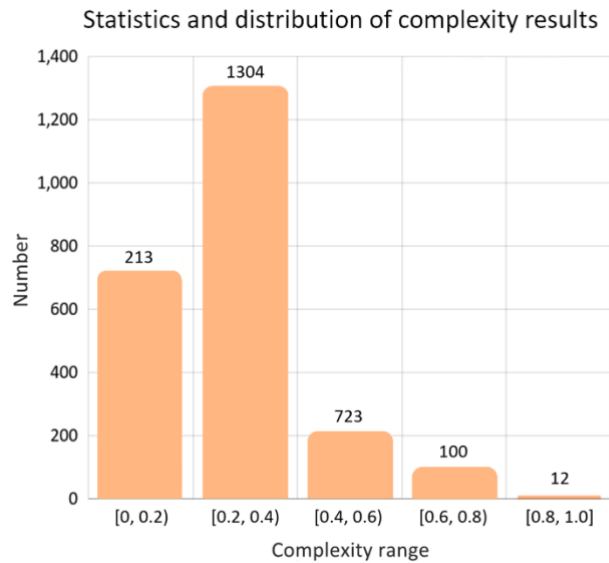


Figure 9. The distribution of complexity values.

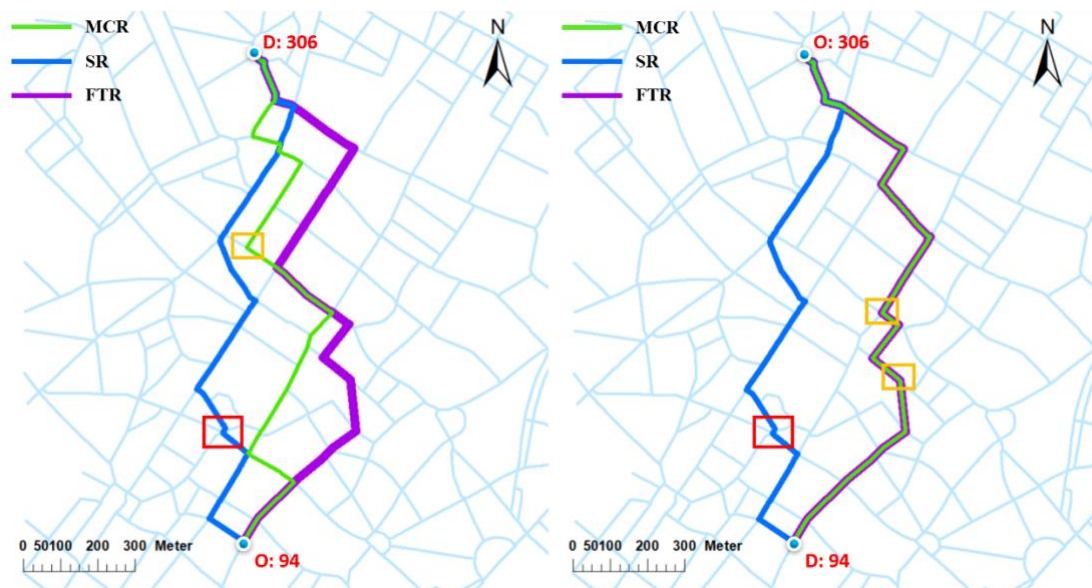
4.3 Results of route planning

4.3.1 Results and Comparisons

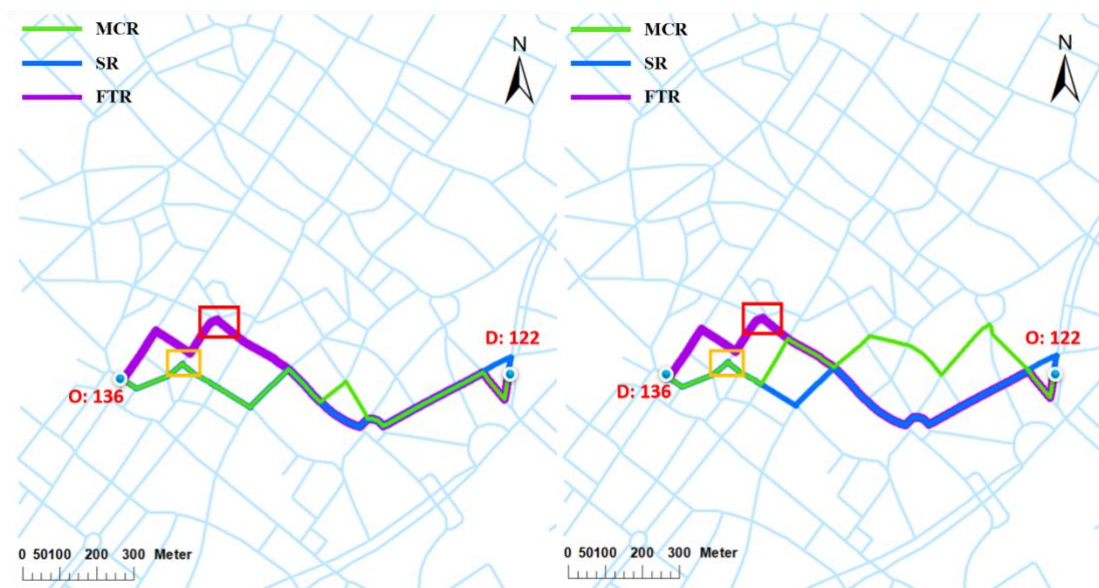
This section compares the results of the proposed minimum total complexity route (MCRs), shortest routes (SRs), and fewest-turn routes (FTRs), aiming to verify the feasibility of the proposed route planning algorithm. This study selected several popular origin/destination (OD) pairs within the study area manually and computed their SRs, FTRs, and MCRs. Afterward, three parameters, including the path length, the number

of turns, and the total complexity value of all intersections, were computed for each generated route.

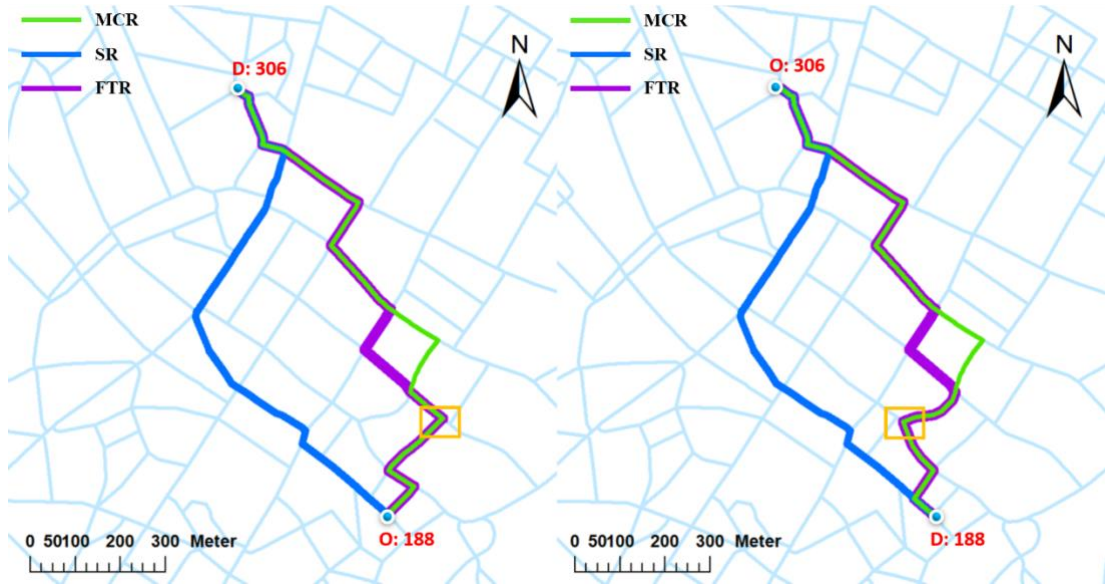
Figure 10 visualizes the generated routes, which illustrates the differences between the MCRs in two directions of OD. Notably, the proposed routing algorithm is capable of evading complex road intersections. For example, the MCRs of OD 94-306, 306-94, 122-136, and 136-122 evade the 5-branch intersection in the study area (i.e., the intersection marked with a red box, which is one of the intersections with the highest decision-making complexity (on average), as shown in **Figure 8**). However, their SRs or/and FTRs cross through that complex intersection. Similarly, the MCRs of OD 188-306, 306-188, 132-222, 222-132, 119-306, and 306-119 all choose those simpler intersections (i.e., the intersection marked with a yellow box, which is one of the intersections with the minimum decision-making complexity (on average) in the study area, as shown in **Figure 8**).



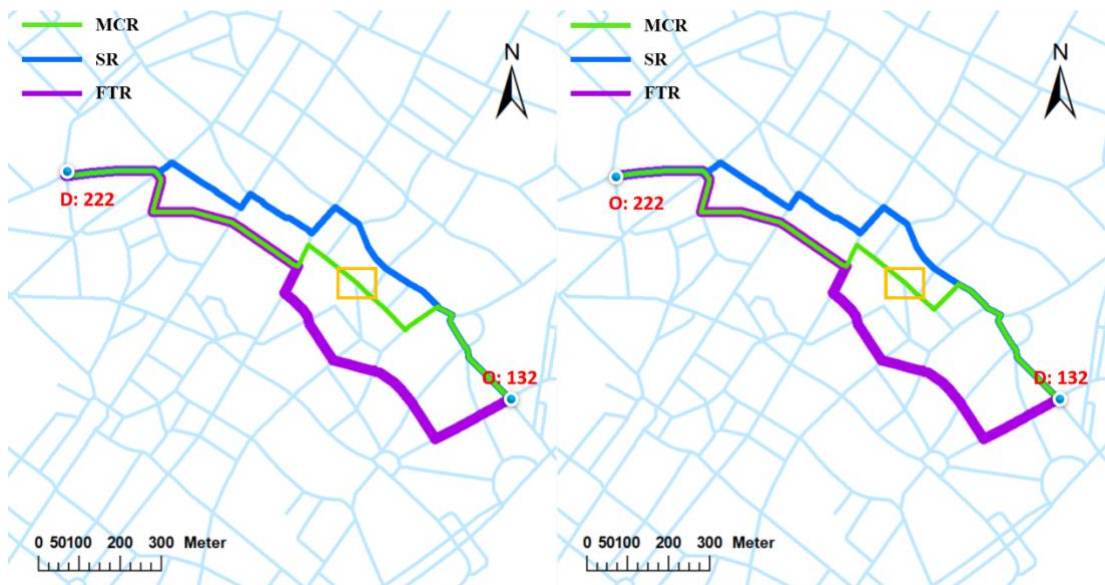
(a) OD pair 1.



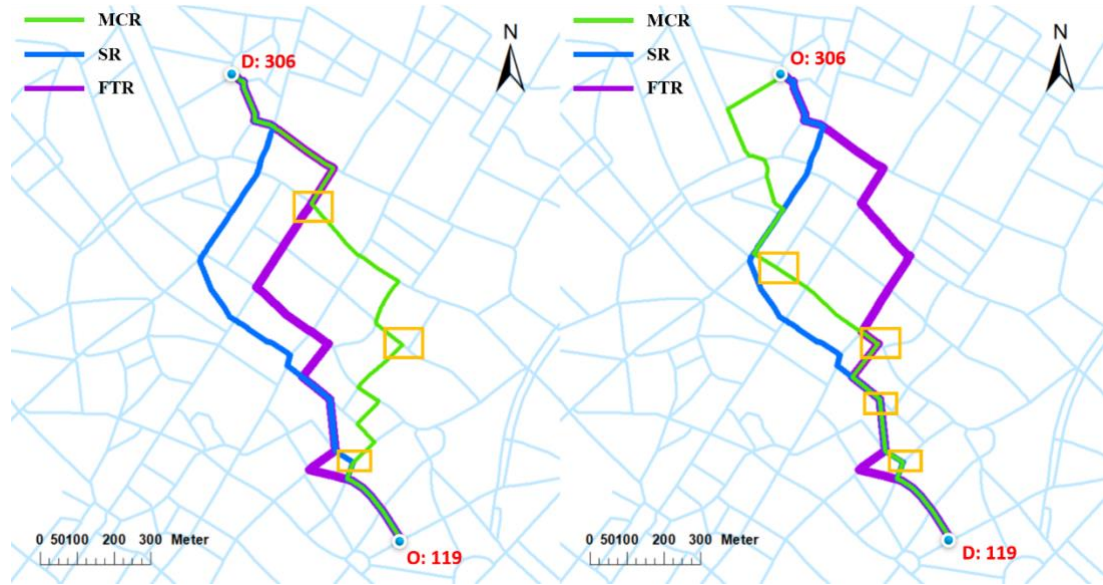
(b) OD pair 2.



(c) OD pair 3.



(d) OD pair 4.



(e) OD pair 5.

Figure 10. The generated routes. A red box indicates a high-complex intersection, while a yellow box represents a relatively low-complex intersection (see **Figure 8**).

Table 2 compares all these routes in terms of their path length, the number of turns, and the total complexity value of all intersections. As expected, the SRs have the lowest path lengths, FTRs have the fewest numbers of turns, and MCRs achieve the minimum total complexity value of all intersections. Compared to the SRs (for the above ten ODs), MCRs are 7.55% longer in path length but have 14.27% less total complexity value. Similarly, compared to the FTRs, MCRs have 1.4 (9.72%) more turns, but are 0.34% shorter in path length and have 7.96% less total complexity value.

Figure 11 visualizes the distribution of the decision-making complexity for each intersection along the generated routes. Two bean plots compare the differences in the distribution of complexity results between MCRs and SRs, and between MCRs and FTRs. The majority of MCRs show the lower distribution of complexity values than SRs and FTRs by the shapes of the bean plots. This also suggests that MCRs are not only superior from a global perspective (i.e., average decision-making complexity) but also in a local complexity at a variety of road intersections.

Table 2. Comparison of three road planning solutions.

No.OD	Method	Parameters		
		Distance	Turns	Total complexity
ODpair 1	SR	1082.46 (0%)	20 (17.65%)	7.07 (18.23%)
#1	FTR	1190.00 (9.93%)	17 (0%)	6.44 (7.69%)
94-306	MCR	1186.37 (9.60%)	20 (17.65%)	5.98 (0%)
ODpair 1	SR	1082.46 (0%)	20 (17.65%)	7.34 (12.40%)
#2	FTR	1173.10 (8.37%)	17 (0%)	6.53 (0%)
306-94	MCR	1173.10 (8.37%)	17 (0%)	6.53 (0%)
ODpair 2	SR	875.96 (0%)	16 (6.67%)	5.87 (9.51%)
#3	FTR	932.95 (6.51%)	15 (0%)	5.56 (3.73%)
122-136	MCR	961.88 (9.81%)	16 (6.67%)	5.36 (0%)
ODpair 2	SR	875.96 (0%)	16 (6.67%)	5.60 (3.70%)
#4	FTR	932.95 (6.51%)	15 (0%)	6.12 (13.33%)
136-122	MCR	919.28 (4.95%)	16 (6.67%)	5.40 (0%)
ODpair 3	SR	830.50 (0%)	16 (33.33%)	4.54 (25.41%)
#5	FTR	895.80 (7.86%)	12 (0%)	3.91 (8.01%)
188-306	MCR	903.18 (8.75%)	12 (0%)	3.62 (0%)
ODpair 3	SR	830.50 (0%)	16 (33.33%)	5.36 (33.00%)
#6	FTR	888.96 (7.04%)	12 (0%)	4.03 (0%)
306-188	MCR	896.33 (7.93%)	12 (33.33%)	4.03 (0%)
ODpair 4	SR	943.73 (0%)	15 (25.00%)	5.03 (24.51%)
#7	FTR	1008.04 (6.81%)	12 (0%)	4.76 (17.82%)
132-222	MCR	978.58 (3.69%)	15 (25.00%)	4.04 (0%)
ODpair 4	SR	943.73 (0%)	15 (25.00%)	5.10 (5.81%)
#8	FTR	1008.04 (6.81%)	12 (0%)	4.93 (2.28%)
222-132	MCR	984.22 (4.29%)	15 (25.00%)	4.82 (0%)
ODpair 5	SR	1077.12 (0%)	19 (18.75%)	6.01 (19.25%)
#9	FTR	1183.85 (9.91%)	16 (0%)	5.99 (18.85%)
119-306	MCR	1182.47 (9.78%)	17 (6.25%)	5.04 (0%)
ODpair 5	SR	1077.12 (0%)	19 (18.75%)	6.25 (23.76%)
#10	FTR	1166.94 (8.34%)	16 (0%)	5.91 (17.03%)
306-119	MCR	1160.03 (7.70%)	18 (12.50%)	5.05 (0%)

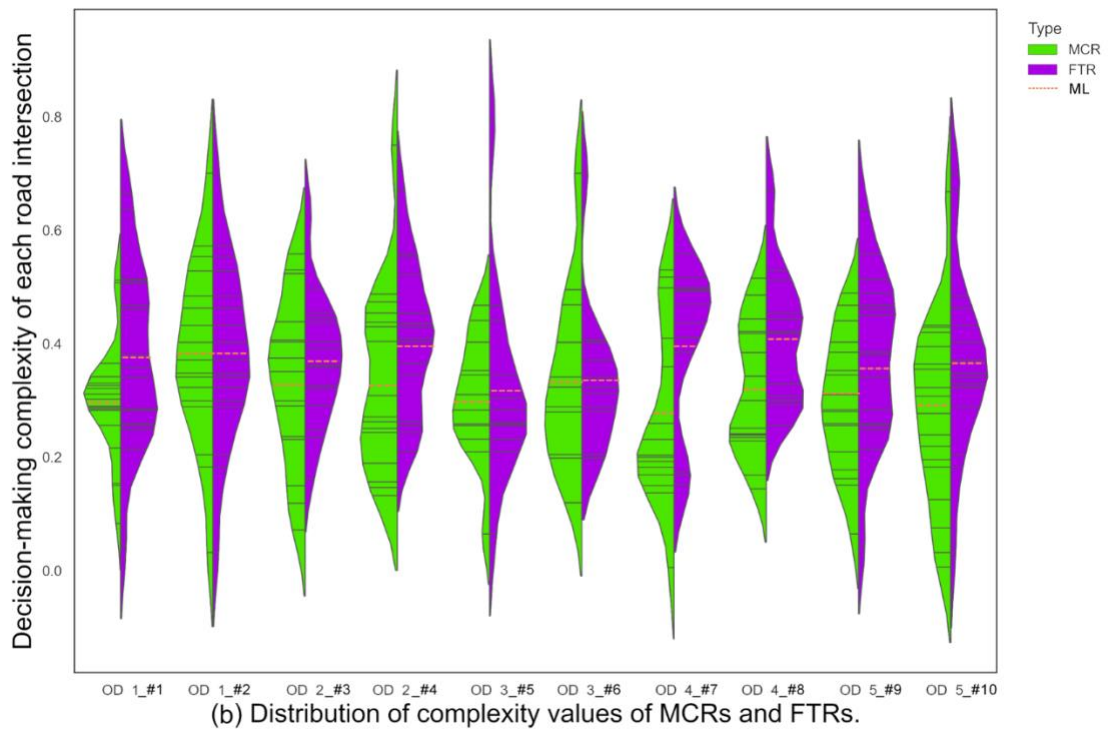
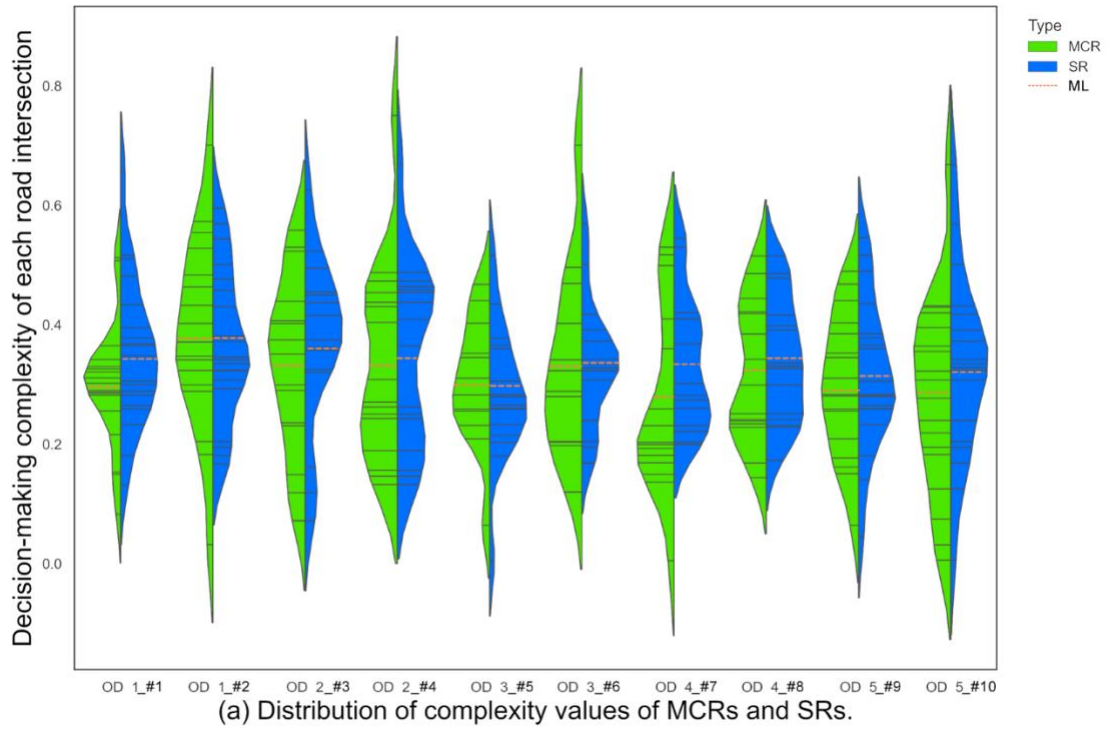


Figure 11. Differences in the distribution of complexity value of each passing road intersection of each generated MCR, SR, and FTR route. Where the black lines in each bean-plot represent the complexity values of intersections of each OD pair route, the orange lines represent the mean line (ML).

4.3.2 Results and comparisons of the whole study area

This section further analyzes and discusses the differences in metrics such as route length and complexity of generated routes based on different route planning algorithms, and explores the correlation between route length and complexity reduction.

Specifically, we generated two route sets (i.e., MCRs and SRs), each with 122,150 routes (i.e., 350×349 OD pairs), using the proposed algorithm and Dijkstra algorithm based on all road network nodes within the study area. Then, the route distances and complexities were compared by groups.

Table 3 shows the comparisons of distance and complexity factors between MCRs and SRs. We divided the results into four distance groups, based on the shortest distance between an OD pair. We focus on two metrics: route distance difference between MCR and SR, and total complexity difference between MCR and SR. The following findings can be highlighted.

- (1) Firstly, compared to the SRs of the four distance groups, the mean distance of the MCRs gradually increased for each group, with an increase of 6.07 meters (1.88%), 32.90 meters (4.39%), 75.64 meters (6.27%), and 118.56 meters (7.27%), respectively, on average 42.78 meters for all routes. Subject to the pre-defined detour threshold δ (i.e., 10%), all routes maintained an increase of fewer than 200 meters. Whereas 90% of the increases ranged from 0 to 105.32 meters, and only 1.15% of the increases exceeded 150 meters, the maximum increase was 191.13 meters.
- (2) Meanwhile, MCRs have a more significant advantage over SRs in the mean total complexity difference (MCD) metric of four distance groups. Specifically, compared to SRs, the complexities of MCRs are decreased by 0.1234 (5.91%), 0.4875 (10.54%), 1.0613 (14.39%), and 1.8758 (18.71%) in the four distance groups, respectively. Via a Spearman Correlation Analysis, we found that the correlation coefficient between route length (i.e., the route length of SRs) and complexity reduction (i.e., the complexity reduction between SRs' and MCRs') is 0.6694 (p-value < 0.001). This suggests that the longer the distance, the bigger complexity reduction the proposed MCR brings.

Table 3. Variation in parameters of MCRs and SRs among the four distance groups.

Distance groups	Distance difference between MCR and SR	Complexity difference between MCR and SR
0-500m	+6.07m (+1.88%)	-0.1234 (-5.91%)
500m-1000m	+32.90m (+4.39%)	-0.4875 (-10.54%)
1000m-1500m	+75.64m (+6.27%)	-1.0613 (-14.39%)
1500m-2000m	+118.56m (+7.27%)	-1.8758 (-18.71%)

In summary, the above results demonstrate that the proposed algorithm is feasible and effective for generating reliable low-complex routes. Moreover, the MCRs can well balance the route length and route complexity.

5 Discussion

Many studies highlighted the importance and need to assess the complexity of urban street environments, particularly at road intersections (Sladewski *et al.*, 2017;

Zhou *et al.*, 2019; Guan *et al.*, 2021). In the field of automotive and pedestrian navigation, the complexity of the street-view environments affects the performances of wayfinding and route following. Complex route intersections increase the difficulty of navigation and even lead to navigation failure and road safety issues. However, computational modelling of the complexity of street-view environments remains challenging due to the lack of feasible approaches to represent street environments' characteristics from human perspectives.

This study presented a novel computational approach to quantify the decision-making complexity of road intersections for enhancing the navigation data models and navigation systems based on specific passing branches, by integrating the environmental characteristics of road intersections in terms of visual, structural, and semantic aspects. Specifically, six features and the extraction methods from various geodata (i.e., street-view panoramic images, road networks, and POI data) were proposed. They can describe distinctive and essential characteristics of road intersections from human perspectives. Furthermore, this study integrated the proposed complexity metric into a route planning algorithm for generating a low-complex route for unfamiliar users. The experimental results match the findings of many existing studies on the complexity of real-world urban environments as well as their impact on human navigation (Krisp and Keler, 2015; Richter, 2009; Zhou *et al.*, 2019). In short, the results demonstrated that the proposed approach can effectively characterize the urban street environments and effectively represent the decision-making complexity of the road intersections from a wayfinder's perspective.

Compared to other related studies which treat each road intersection as a unit and output a single complexity value for each intersection, this work offers a finer complexity quantification for each intersection, considering the entry and exit branches when passing this intersection. This potentially provides more realistic results from a wayfinder's perspective, as different navigation experiences can be expected when crossing the intersection using different entry and exit branches.

The proposed complexity quantification method can potentially serve navigation route planning and communication tasks, such as generating a low decision-making complexity route for unfamiliar users. In this work, we illustrate how a route with a low complexity value can be identified while maintaining a reasonable route distance. The case study shows that the proposed algorithm can select a route that avoids complex road intersections. The proposed complexity metric can be also used to generate a high-complexity route for driving training and testing (e.g., of human drivers or unmanned systems). Furthermore, it can be applied to the perception and understanding of the physical environments by identifying the critical locations where humans might encounter navigation difficulties (or traffic safety issues) and providing more detailed navigation guidance and early-warning signals to assist users at these critical locations. In addition, this study can quantify the multidimensional characteristics of the road environment, which can be used to assess urban environments from a human perspective and to support sustainable urban and environmental development.

Several limitations of this work should be also noted. Firstly, due to the complexity of designing a user experiment to evaluate the proposed complexity metric and the

routing results, we mainly evaluate our methodology via a proof-of-concept (without human participants). Even though the evaluation shows the results are in line with common sense and existing findings in the literature, it might be still interesting to evaluate the methodology via a user study, for example, in a virtual reality (VR) setting. Secondly, currently, we simply combine the visual, structural, and semantic features using a weighted sum approach. Employing different weights might affect the results. For example, a higher visual weight might reduce the effect of structural features on the results. In this case, those branches with similar visual characteristics will lead to higher decision-making complexity. Similarly, a higher semantic weight will assign lower complexity values for branches with well-known POIs. While the weighted sum approach is commonly employed in the literature, it also makes sense to explore other methods to combine these features, e.g., using machine learning-based approaches (if human labelled “ground-truth” data are available). It might be also useful to consider individual differences in responsiveness and sensitivity to the different proposed environmental features, considering gender aspects as well as cognitive abilities and preferences across age groups. Furthermore, considering that street environments might look differently in different seasons, it will be very interesting to apply the proposed method with street-view images from different seasons and analyze whether different seasons lead to different decision-making complexity. Future research should also consider the issue of "cumulative" complexity based on navigation big data, especially in the context of route planning, for further comparisons and validations in terms of effectiveness.

6 Conclusions

Existing computational methods for quantifying the decision-making complexity of road intersections fail to consider specific passing branches and do not fully incorporate physical environmental characteristics in visual, structural, and semantic aspects, resulting in a poor match between the quantified score and the actual decision-making complexity perceived by humans. This study proposed a series of visual, structural, and semantic features to quantify the complexity of a road intersection, considering the entry and exit branches for passing the intersection. The metric was further integrated into a route planning algorithm to generate a low-complexity route that avoids complex road intersections.

The proof-of-concept evaluation results show that the proposed method can quantify the decision-making complexity by incorporating the environmental characteristics of the road intersections and the specific passing branches. The complexity results can serve as a valid measure of the physical environments and effectively represent the human-oriented complexity modelling of road intersections.

Regarding future work, it makes sense to further refine the proposed model by incorporating personalized attributes and characteristics of users and quantifying their cognitive habits and preferences for better adaptive weighting of each dimension. Furthermore, it is also interesting to integrate the proposed method into navigation systems and urban environmental assessments, e.g., to provide adaptive navigation

guidance according to the complexity of a road intersection, or to improve the design of road intersections to facilitate human behavior in these environments.

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