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# Indoors Positioning Based on Spatial Relationships in Locality Description

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**ABSTRACT** Spatial relationships exist in our daily communication and provide many locality clues, but minimal attention has been devoted to positioning localities indoors with spatial relationships extracted from locality descriptions. Locality description generally contains spatial relationships (i.e., topological, distance, and direction relations) and reference objects (ROs). For locality description positioning, distance and direction relation convey more clue than topology and combined together can provide much clue to positioning. Explicit and implicit features are inherent characteristics of locality descriptions. Based on the analysis of locality descriptions, a classification scheme of indoor locality descriptions is provided. To address the positioning locality with spatial relationships, we propose a two-state method. First, the located region is obtained according to the fuzzy region of spatial relations in locality description. Second, the probability distribution is determined, which is a joint probability function that consists of relative direction and distance (quantitative or qualitative distance) membership functions. The relative direction membership function is conducted based on human's direction cognition is related to angular information. The trapezoid quantitative distance membership function is based on indoor cognitive experiment. The qualitative distance membership function for indoor ROs is based on minimum Euclidean distance and stolen area. From the cognition and computation perspectives, the visible boundary met some restrictions is provided and a sampling method is defined. To obtain the unique positioning locality, a principle is proposed. We evaluate our method by conducting an indoor cognitive experiment and demonstrate that a positioning accuracy of 3.50 m can be achieved with semantically derived spatial relationships.

**INDEX TERMS** Spatial relationships, membership function, positioning localities indoors, locality description.

## I. INTRODUCTION

In recent years, with the ongoing development of cities and the Internet, people spend much more time (almost 80%) indoors [1]. The demand for location-based services (LBS) is increasingly diversified, and indoor location positioning has been developing rapidly [2]. Currently, indoor positioning technology that uses single or multiple physical sensors is complex [3], [4]; positioning is unstable [5] and requires

expensive equipment [6]. Under the background of artificial intelligence, with the development of positioning technology, the demand for indoor positioning is no longer simply a function of high precision but includes better integration with intelligent terminal equipment and intelligent services [7]. Therefore, it is of great practical significance to develop an intelligent, low-cost, indoor positioning method under the premise of accounting for positioning accuracy.

Indoor positioning services for people should address their feedback and needs [7], such as locality descriptions not only associated with navigation, but also with daily

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communication [8]. The development of cognitive technology, natural language understanding, and voice recognition technology has made communication between people and machines more mature [9], [10]. The interactions between people and machines will become more intelligent and easier with time. Natural language interactions via voice or text will be the future direction of LBS [10].

As one form of natural language, locality descriptions exist in our daily communication. In general, locality descriptions include reference objects (RO), spatial relationships (SR), and target objects (TO). Any named feature can be called a reference object. Spatial relationships in Geographic Information System (GIS) commonly involve three components, namely, distances, directions and topological relations [11]. Compared to GIS, locality descriptions focus more on direction and distance relations than topological relations [12]. Describing locality, distance and direction together provides more locality cues, which avoids ambiguities or uncertainties [13].

In recent years, although positioning methods based on locality descriptions have made great progress [14]–[15], there are still deficiencies in the study of spatial relation uncertainty modelling and computational methods for complex locality description scenes. In this paper, to address the bottleneck problem of locality description positioning, an indoor shopping market is taken as an example to study uncertainty modelling and a positioning method based on the spatial relationships in indoor locality descriptions. This paper proposes a computational method for indoor positioning with spatial relations extracted from locality descriptions. Specifically, we provide a modelling method for indoor spatial relations, *i.e.*, relative direction, quantitative distance and qualitative distance. Our main contributions are threefold:

(1) From a modelling perspective, this paper provides modelling methods for relative direction, quantitative distance and qualitative distance relations, which are based on fuzzy set and can be used for indoor positioning.

(2) From a methodological perspective, the paper contributes a two-stage computational method that includes obtaining a located region and describing a probability distribution, which are based on an indoor locality description analysis and classification.

(3) From an application perspective, this paper proposes an innovative use of spatial relations in locality descriptions for indoor positioning, which provides a theoretical basis and technical support for indoor positioning based on voice location descriptions.

The remainder of this paper is organized as follows. Section 2 reviews related works on indoor positioning, locality descriptions and spatial relations (*i.e.*, distance and direction relations). Section 3 presents indoor spatial relations modelling, including relative direction, quantitative distance and qualitative distance. Section 4 provides the architecture of indoor locality description and the resulting positioning method. Examples are provided to demonstrate our method

in Section 5. Finally, Section 6 summarizes the study and discusses future research directions.

## II. RELATED WORK

### A. INDOOR POSITIONING

Recent years have witnessed much work on the development of indoor positioning technologies. Earlier work on indoor positioning focused on single positioning technology, such as iBeacon, Wi-Fi, camera, radio frequency identification [16]–[19]. iBeacon-based and RFID-based positioning method can provide a high-precision positioning for pedestrians in an indoor environment. But the high-precision positioning depends on the layout density of equipment, and their costs are always very high for a wide coverage area [20]. Due to the worldwide availability of Wi-Fi access point, the Wi-Fi fingerprint localization technology has become the most popular indoor positioning (AP) method [21]. However, it is still expensive to maintain a Wi-Fi-based positioning system because of the working status of Wi-Fi APs and the unexpected changes in the position [22]. Camera-based (*i.e.*, visual-based) positioning method can be divided into recognition-based image geo-localization method and geometric matching-based method [23], which can provide enough positioning accuracy in intricate indoor environment. But this method is complex in algorithm.

With the improvement in computing and storage performance on smart phones, the sensor-fusion-based indoor positioning method attracts lots of attention. Li *et al.* [24] provided a hybrid pedestrian navigation algorithm based on investigation of different combinations of pedestrian dead-reckoning (PDR), Wi-Fi fingerprinting, and magnetic matching (MM), which overcame the single-source drawback. To deal with the complex spatial topology and RF transmission environment, an indoor scene constrained method for localization is proposed in [25], which integrates cameras, Wi-Fi and inertial sensors. The fusion results show that the accuracy and stability of the system are better than those of an independent positioning source. However, it not only increases positioning and technical costs, but also increases the power consumption of the positioning terminal and decreases the service capacity.

Based on the above statement, indoor positioning technology has disadvantages of complicated algorithms, unstable positioning, high cost. Therefore, exploring new positioning source accounts for positioning accuracy and cost is meaningful.

### B. LOCALITY DESCRIPTION

Locality description answers a “where” question [26]. Humans describe localities in a hierarchical manner, whether the location is indoors or outdoors [27]. Locality description reflects a human’s direct or indirect interaction with the environment and uncertain is inevitable. There are reference objects, spatial relations and target objects in locality descriptions [11], [15]. Generally, there is at least one

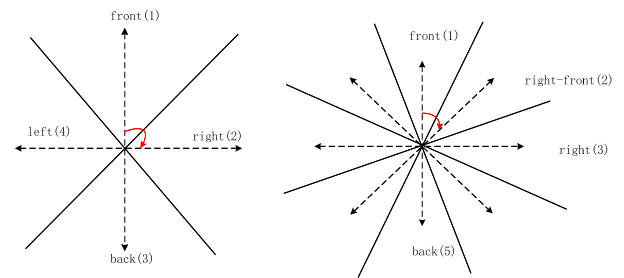
reference object and its spatial relations in a locality description [28]. Spatial relations include topological relations, distance relations and direction relations, which convey locality clues [11]. Compared to distance and direction relations, topological relations convey rough locality information and can be reflected by the distance and direction relations [11]. To avoid ambiguities, distance and direction are usually combined in locality descriptions, such as “object A is 100 m in front, and object B is 50 m to the right” [13]. However, locality descriptions are complex, either explicitly or implicitly [27], such as “object A is 100 m in front, and object B is to the right” implies that “object A is 100 m in front, object B is to the right and object B is near me”.

Another area of research on locality description is the positioning method. The most commonly used method is the “Point” method, which uses a single coordinate to locate a feature whether it is polyline or polygon [29]. Wieczorek [29] developed a Point-Radius method to combine all kinds of uncertainty into a ratio that ignores the shape of the RO. The shape method is conceptually simple, but the geometry that it represents is complex and excludes the original locality description. Guo *et al.* [11] proposed the concept of uncertainty of a field to represent the uncertainty of ROs and spatial relationships, and presented a probability method to georeference localities. Considering the shape of the RO, Liu *et al.* [15] proposed a probability method and refined operation that combine a set of uncertainties. Since then, many scholars have performed related research [14], [30], [31].

### C. SPATIAL RELATIONS

#### 1) DIRECTION RELATION

Prior studies have modelled direction relations from various perspectives. At least three methods can be identified from the related literatures. One method is attentive to the absolute direction, which is based on an absolute spatial reference system (ASRS) [32]. The absolute direction can be qualitative (e.g., north) and quantitative (e.g., 45°) [15], of which quantitative direction is mainly used in special applications (e.g., species data, earthquake data) [14], [30]. The cardinal direction relationship (CDR) is one of the most influential relationships, which divides the space into four or eight cones according to different contexts. Since then, many direction models have been developed for different applications and scales [33]. The second method focuses on relative direction. Krishnapuram [34] argued that the cones that one person searches from one direction to another are related to angular information, and the distance is unimportant during the process. Based on this, relative direction membership functions (that is, right, left, above, etc.) were defined. Bloch [35] extended the “between” relation to medical images and defined the concept of visibility. Accordingly, “surround” and “along” relations are modelled based on fuzzy sets in image understanding [36], [37]. The third method focuses on the computation of the direction relation, which has always



**FIGURE 1.** Illustration of path ( $\Theta$ ): red arrow indicates the clockwise direction.

been the focus of many scholars. A histogram of angles is proposed to calculate the relative directions of objects [38]. To overcome the drawbacks of a histogram of angles, which has computational cost and is only suited for raster data, Matsakis [39] utilized a histogram of force. Since then, this notion has been better developed [40].

#### 2) DISTANCE RELATION

Distance relations in locality descriptions can be divided into qualitative distances and quantitative distances. Qualitative distance refers to terms such as “near” or “far”, for which different people have different understandings according to different scales. Given the conceptual membership function of the qualitative distance “near”, Liu argued that the greater the distance target object (TO) from the reference object (RO), the less likely “near” would be described. Additionally, without considering other factors, there is an intersection point between the conceptual membership function of “near” and “far” [15]. Krishnapuram proposed a “near” and “far” membership function and argued that “near” is a complement to “far” [34]. Based on a human-participants study, Worboys discussed the vague spatial relation “near” in environmental space and presented three approaches (i.e., fuzzy nearness, distance measures and four-valued logic) to analyse it [41]. After a discussion of context factors that affect the relationship between qualitative distance in linguistic and metric distance measures, Yao applied Ordered Logit Regression (OLG) to proximity modelling [42]. Schockaert collected unstructured and semi-structured data that were available on the web and designed a computational framework to represent the near relation based on a fuzzy set [43]. Brennan drew on a Generalized Voronoi Diagram to qualitatively represent the “near” relation [44]. Building on this work, Gong provided a mixed membership function that is based on Voronoi stolen area and Euclidean distance to model near relations, but did not apply it further [45]. Wang *et al.* [46] provided the near relations used in landmark reference system (LRS), but not discussed other complex description scenes and only discussed the LRS in one floor.

Compared to qualitative distance, quantitative distance is a numeric distance used in practice and uncertainty is an inherent characteristic. In the work proposed by Liu *et al.* [15], the uncertainty of quantitative distance due to measurement error or record imprecision is comprehensively discussed.

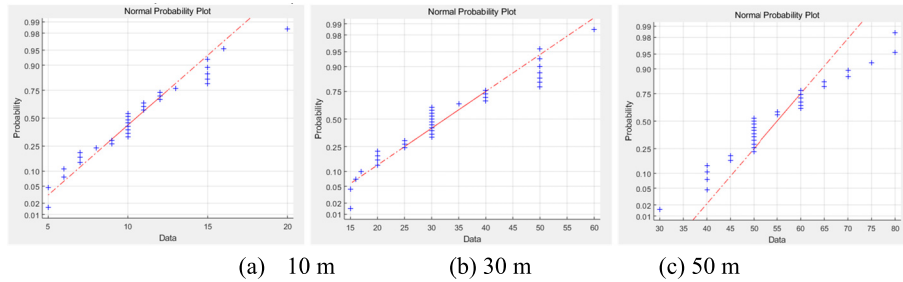


FIGURE 2. Normal test.

The quantitative distance in locality descriptions for species data or Search and Rescue (SAR) confirms to record imprecision, so Barve [47] and Doherty *et al.* [14] used this model to locate places. Conducting a cognitive experiment, Wang *et al.* [13] determined that the uncertainty of numeric distance derived from measurement error is consistent with a normal distribution.

Based on the above analysis of prior research, the method of modelling distance relations can be summarized into three components: (1) Cognitive experiments, which are based on subject experiments but are labour-intensive and time-consuming; (2) geographic information retrieval (GIR), which focuses on unstructured data on the web but is limited to the density of the population; and (3) spatial geometry, which is simple but has no practical application.

### III. MODELLING INDOOR SPATIAL RELATIONS

The modelling method for indoor spatial relations is based on fuzzy set and spatial cognition. A fuzzy set in a universe X is formally defined as a mapping U from X to the unit interval [0, 1]. For relative direction, it is based on human’s direction cognition is related to angular information. For quantitative distance, it is based on cognition experiments and conforms to normally distribution. For near relation, it is based on stolen-region and Euclidean distance, which consistent with fuzzy set.

#### A. RELATIVE DIRECTION

Indoors, where there is a lack of absolute references, people frequently tend to use relative directions. Additionally, people’s orientations are related to angles [34]. For example, when turning from the front to left-front, the angle is approximately 45°. Based on such spatial cognition, we provide a relative distance membership function  $P_{RelDir}(\Theta)$ , for which the function should be different according to different contexts.

$$P_{RelDir}(\Theta) = \begin{cases} 1 & \left| \frac{\pi}{4} \times \text{path}_{(\Theta)} - \Theta \right| \leq a \\ \frac{\frac{\pi}{8} + \left| \frac{\pi}{4} \times \text{path}_{(\Theta)} - \Theta \right|}{\frac{\pi}{8} - a} & a \leq \left| \frac{\pi}{4} \times \text{path}_{(\Theta)} - \Theta \right| \leq \frac{\pi}{8} \\ 0 & \left| \frac{\pi}{4} \times \text{path}_{(\Theta)} - \Theta \right| \geq \frac{\pi}{8} \end{cases} \quad (1)$$

Equation (1) [34] is based on the assumption that the space is divided into eight cones, i.e., front, left, right, back, front-left, front-right, back-left, and back-right.

$$P_{RelDir}(\Theta) = \begin{cases} 1 & \left| \frac{\pi}{2} \times \text{path}_{(\Theta)} - \Theta \right| \leq a \\ \frac{\frac{\pi}{4} + \left| \frac{\pi}{2} \times \text{path}_{(\Theta)} - \Theta \right|}{\frac{\pi}{4} - a} & a \leq \left| \frac{\pi}{2} \times \text{path}_{(\Theta)} - \Theta \right| \leq \frac{\pi}{4} \\ 0 & \left| \frac{\pi}{2} \times \text{path}_{(\Theta)} - \Theta \right| \geq \frac{\pi}{4} \end{cases} \quad (2)$$

Equation (2) is based on the assumption that the space is divided into four cones, i.e., front, left, right and back.

In Figure 1, the space is divided into four and eight cones according different contexts. The dashed lines are the center lines of corresponding cones, and each center line in assigned a number in the clockwise direction. In Equations (1) and (2), the parameter  $\text{path}_{(\Theta)}$  is the minimum path between two different center lines of corresponding cones. For the place description “object A is 50 m in front, object B is in the left-front”, the  $\text{path}_{(\Theta)} = 2$ .

#### B. QUANTITATIVE DISTANCE

Quantitative distance in locality description is based on visual cognition and measurements, which confirms a normal distribution. According to [13], cognitive experiments are conducted to model quantitative distances (10 m, 30 m, 50 m). In the experiments, each group distance has two marked points (i.e., straight or inclined, which is almost 45°), and participants are asked to stand at the marked points to describe the distances between the marked points and reference objects. The participants have different backgrounds, and their ages range from 15 to 52. All related data are collected, and overestimated data are eliminated. After normal tested (Figure 2), each group’s cognitive distance conforms to a normal distribution (Figure 3).

To model the quantitative distance, we provide a trapezoid function ( $P_{Dis}(d)$ ) [46] based on fuzzy set, which is intuitive-

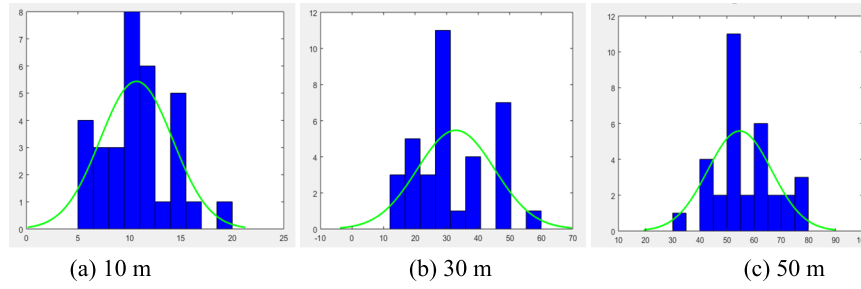


FIGURE 3. Normal distribution.

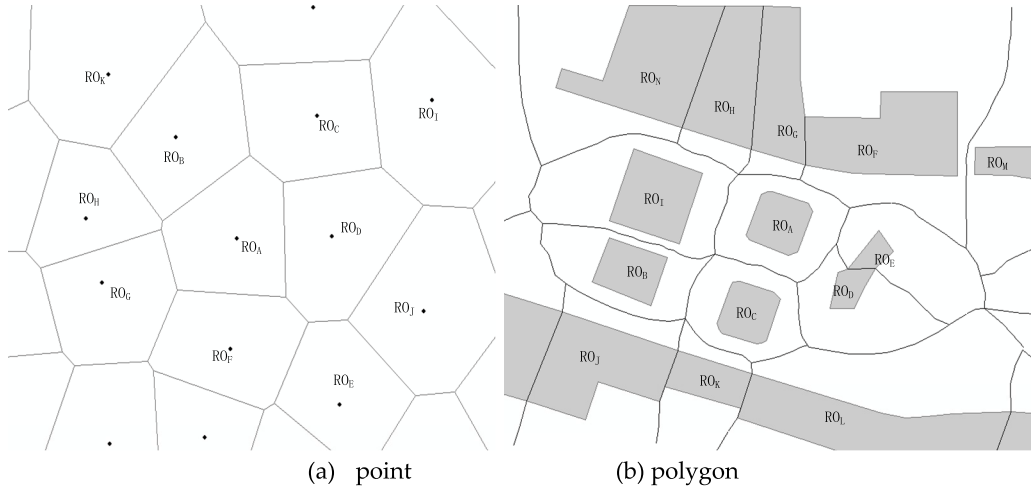


FIGURE 4. Neighbours of  $RO_A$ .

ness, robustness, and computation efficiency.

$$P_{Dis}(d) = \begin{cases} 1 & n \leq d \leq k \\ (n - m)(d - m) & m \leq d \leq n \\ (k - l)(d - l) & k \leq d \leq l \\ 0 & otherwise \end{cases} \quad (3)$$

The paraments  $n$  and  $k$  are the deviations from the right distance, and  $m$  and  $l$  can be derived from the normal distribution of quantitative distance.

### C. QUALITATIVE DISTANCE

**Definition 1 Neighbours of RO:** For a set of entities, if two entities share a common edge of a Voronoi diagram, they neighbour each other. In Figure 4, point  $RO_A$  neighbours  $RO_B, RO_C, RO_D, RO_E, RO_F, RO_G, RO_H$  and polygon  $RO_A$  neighbours  $RO_B, RO_C, RO_D, RO_E, RO_F, RO_G, RO_H, RO_I$ . The neighbours of  $RO_1$  are denoted with  $neighbor(RO_1)$ . i.e., for point  $neighbor(RO_A) = \{RO_B, RO_C, RO_D, RO_E, RO_F, RO_G, RO_H, RO_I\}$ , and for polygon  $neighbor(RO_A) = \{RO_B, RO_C, RO_D, RO_E, RO_F, RO_G, RO_H, RO_I\}$ .

**Definition 2. Neighbouring area of RO:** The neighbouring area of RO refers to the region of a site (TO) that is inserted into and neighbours RO. The neighbouring area of R is defined as  $NeighborArea(RO)$ .

The Delaunay triangulation is the “dual” of the Voronoi diagram. The vertex of the Voronoi diagram is the center of

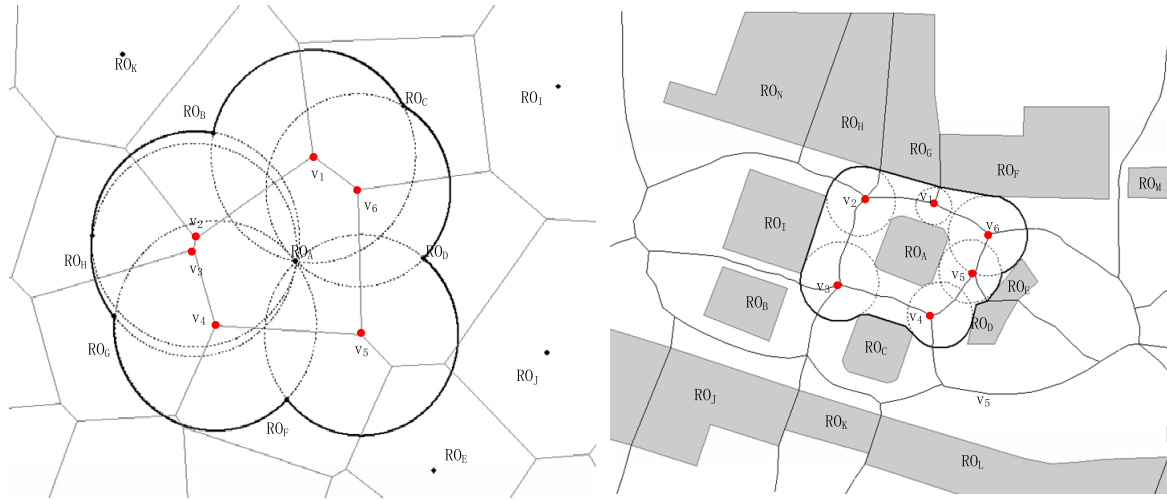
the circumcircle of its related Delaunay triangulation. For a point set, of which  $neighbors(RO_A) = \{RO_B, RO_C, RO_D, RO_E, RO_F, RO_G, RO_H\}$ , the vertices of the Voronoi region of  $RO_A$  are  $v_1, v_2, v_3, v_4, v_5$  and  $v_6$ . The neighbouring area of  $RO_A$  is the union of circle arcs that are parts of the circumcircle that is centered on the vertices of the Voronoi region (as shown in Figure 7). For polygon entities, of which  $neighbors(RO_A) = \{RO_B, RO_C, RO_D, RO_E, RO_F, RO_G, RO_H, RO_I\}$ , the vertices of the Voronoi region of  $RO_A$  are  $v_1, v_2, v_3, v_4, v_5$  and  $v_6$ . The neighbouring area of  $RO_A$  not only consists of circle arcs but also the segments of its neighbours (as shown in Figure 5).

**Definition 3. Stolen-region:** The stolen-region refers to the region that is part of the Voronoi region of the original RO but now belongs to the Voronoi region of TO, after a new site is inserted into the existing Voronoi diagram (Figure 6).

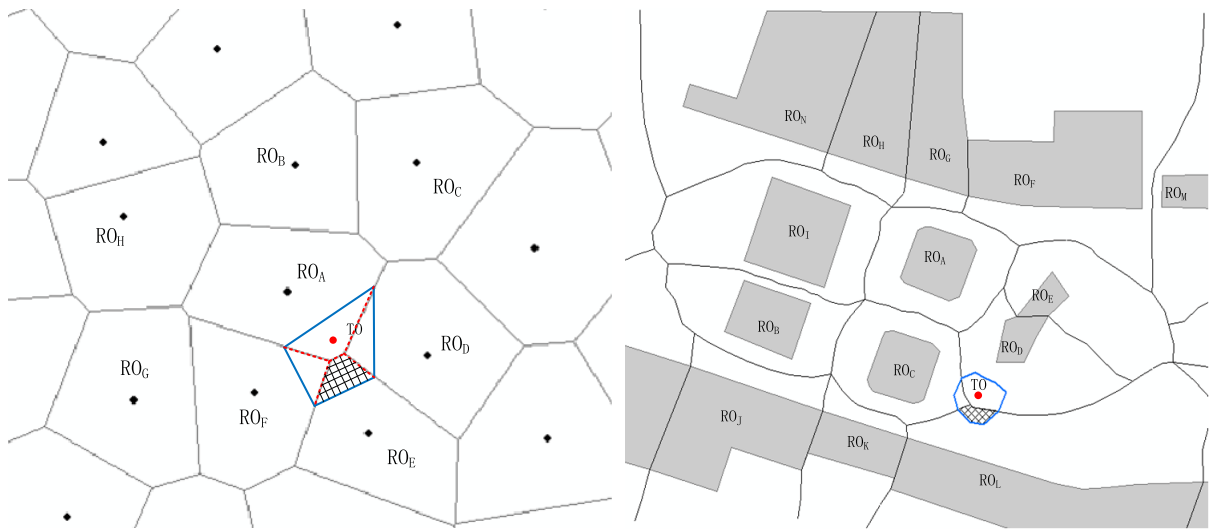
Based on stolen-region and Euclidean distance [45], the near relation membership function for polygon ROs,  $P_{Near}(t, RO_i)$ , is provided:

$$P_{Near}(t, R_i) = \frac{\frac{Reg_i}{\min d(t, RO_i)^2}}{\sum_{R_k \subset neighbor(t)} \frac{Reg_k}{\min d(t, RO_k)^2}} \quad (4)$$

In the equation defined above,  $t$  represents TO,  $t \in NeighborArea(RO_i)$ , and  $\min d(t, RO)$  is the squared minimum distance between  $t$  and  $RO_i$ .  $Reg_k$  represents the region stolen from  $RO_k$  by  $t$ . The equation holds the following four



**FIGURE 5.** Neighbouring area of  $RO_A$  (a) point and (b) polygon. The black solid region is the neighbouring area of  $RO_1$ . The dashed-line circle centred on the vertices of the Voronoi region is the circumcircle of a triangle consisting of the three points closest to the vertex.



**FIGURE 6.** Illustration of stolen region. (a) The area delineated by a blue line is the area stolen from  $RO_A$ ,  $RO_D$ ,  $RO_E$  and  $RO_F$ ; the dashed area is the area stolen from  $RO_E$ ; (b) the area delineated by a blue line is the area stolen from  $RO_C$ ,  $RO_L$ , and  $RO_D$ ; the dashed area is the area stolen from  $RO_L$ .

constraints, which are based on fuzzy set mapping of the near relation to interval  $[0, 1]$ . In the four constraints,  $x$  and  $y$  denote the coordinate of  $t$ . *Constraint 1* indicates that the position of the  $t$  can be described by the ROs neighbour to  $t$ . *Constraint 2* implies that when  $t$  is at the position of  $RO_i$ , its probability is 1. *Constraint 3* shows the boundary of the near relation of  $RO_i$ . *Constraint 4* means that the near relation membership function of  $RO_i$  is continuous.

Constraint 1:

$$\sum_{R_i \in \text{neigh}(t)} P(x, y, R_i) = 1 \quad (5)$$

Constraint 2:

$$P(x, y, R_i) = 1 \quad (6)$$

Constraint 3:

$$P(x, y, R_i) = 0, \forall (x, y) \notin \text{NeighborArea}(R_i) \quad (7)$$

Constraint 4:

$$\lim_{(x-x')^2+(y-y')^2 \rightarrow 0} (P(x, y, R_i) - P(x', y', R_i)) \rightarrow 0 \quad (8)$$

## IV. METHOD

### A. OVERALL ARCHITECTURE

The features of indoor and outdoor locality descriptions are similar. Combining distance and direction relations provides more locality clues to avoid ambiguous descriptions. From the cognitive linguistics perspective, there are at least one and at most three reference objects with related spatial relationships in locality descriptions (Figure 7). However, one reference in a locality description (i.e., scene 1) cannot be known with regard to its relative direction and thus does not provide many clues with regard to positioning. Locality descriptions are complex, either implicitly or explicitly [27].

TABLE 1. Explicit locality description.

Scene	Example
Scene 2	e.g., “object A is 50 m in front, object B is 30 m to the left”
Scene 3	e.g., “object A is 50 m in front, object B is 30 m to the left, object C is 30 m to the front-left”

TABLE 2. Implicit locality description.

Scene	The number of reference objects lacking quantitative distance	Example
Scene 2	One	e.g., “object A is 50 m in front, object B is (near) to the left”
	Two	e.g., “object A is (near) in front, object B is (near) to the left”
Scene 3	One	e.g., “object A is 50 m in front, object B is 30 m to the left, object C is to the front-left”
	Two	e.g., “object A is 50 m in front, object B is (near) to the left, object C (near) is to the front-left”
	Three	e.g., “object A is (near) in front, object B (near) is to the left, object C (near) is to the front-left”

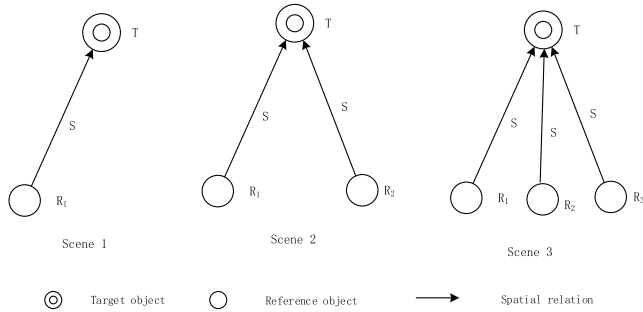


FIGURE 7. Conceptual diagram of indoor locality description.

From the cognitive psychology perspective, when the RO lacks a related quantitative distance, the RO tends to be near the human [28], [48]. For this situation, we consider the near relation as a potential location clue to assist in positioning.

Based on the above analysis, we focused on scenes 2 and 3 and divided the locality description into explicit and implicit according to the complete of quantitative distance in the locality description, as shown in Tables 1 and 2.

*Explicit Locality Description:* The quantitative distance and direction relations of reference objects in the locality description all are equipped.

*Implicit Locality Description:* At least one reference object related to the quantitative distance in the locality description is lost.

We developed a two-stage computational method that takes ROs and their related spatial relations as inputs and then outputs the positioning location. The first stage is to obtain the located region by the intersection of distances in locality description, and the second stage is to describe the probability in the located region. The method was designed based on the theory of probability and spatial cognition. The joint probability is a statistical measure that calculates the likelihood of two events occurring together. In our method, the joint

probability is employed to integrate all position clues in position description. The position clues can be divided into distance and direction relations. The distance and direction probability in located region can be calculated according to the number of direction and distance relations in the classification scheme of indoor locality descriptions. In other words, the positioning method is a joint probability function consists of distances and directions membership functions. Spatial cognition is a branch of cognitive psychology that studies how people acquire and use knowledge about their spatial environment, including location, distance, direction, pattern, and movement. To calculate the direction and distance between ROs, visible boundary, i.e. the segment of RO and can be seen from the current location, is introduced considering spatial cognition to improve the computation efficiency [35]. Figure 8 shows the overall architecture of the method. Figure 8 shows the overall architecture of the method. We focus on the computational method and it is given as follow.

**B. STAGE 1: OBTAINING THE LOCATED REGION**

*Definition 5. Fuzzy Band:* A band with outer and inner rings around the RO corresponds to upper and lower of quantitative distances, denoted as a Fuzzy Band. This is shown in Figure 9.

*Definition 6. Located Region:* The region in which the locality description may be located. It is the intersection of the distance region in the explicit or implicit locality description (the quantitative distance and qualitative distance regions respectively correspond to the fuzzy band and neighbouring area), denoted as Located Region. This is shown in Figure 9.

**C. STAGE 2: PROBABILITY DISTRIBUTION**

*Definition 7. Visible Boundary:* The segment of RO that can be observed from the described location, which should meet some restrictions from cognition, denoted as Visible\_Bdy.

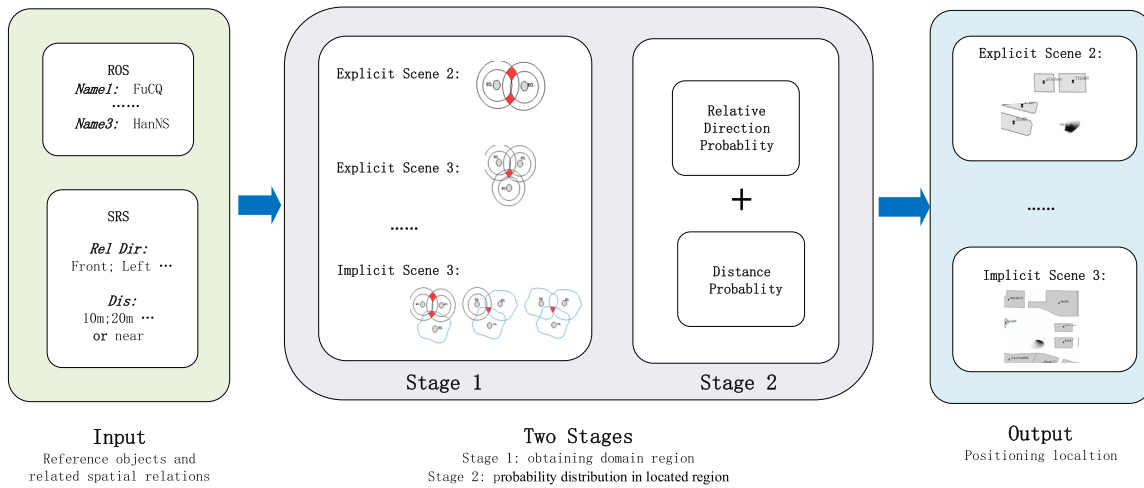


FIGURE 8. Overall architecture of the method.

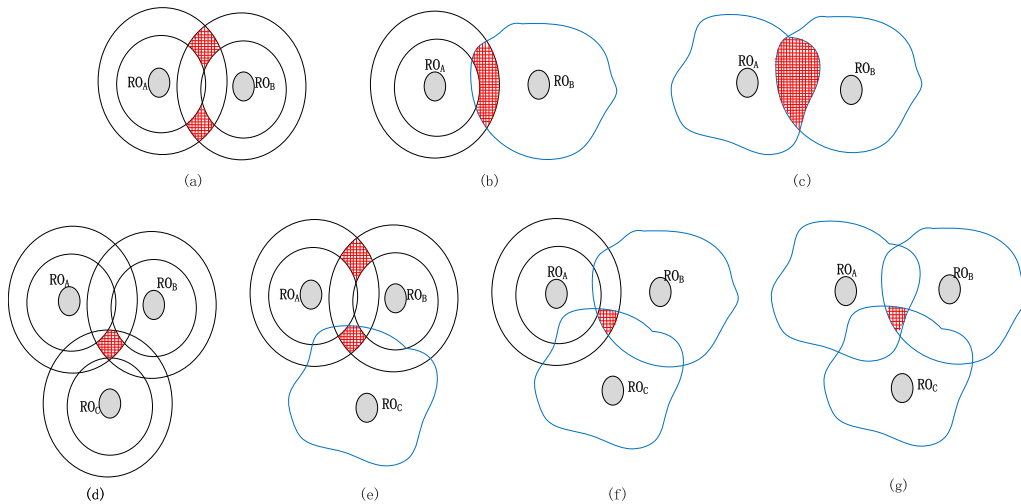


FIGURE 9. Definitions of the fuzzy band and located region; the black line bands correspond to the fuzzy bands of reference objects; the blue line region corresponds to the neighbouring areas of reference objects; the region with the red grid corresponds to the located region (a, b and c are illustrations of scene 2; d, e, f and g are illustrations of scene 3).

The acquisition of the visible boundary of RO for quantitative and qualitative distances are different. The former can be obtained by the intersection of a circle with its upper distance as the radius and can describe the location as a center with a boundary of its reference object. Based on the segment, visible and cognition restrictions are conducted. The acquisition of the visible boundary of qualitative distance is directly conducted, with visible and cognition restrictions on the boundary of the reference object.

**Visible Restriction:** The visible boundary should not be occluded, as shown in Figure 10.

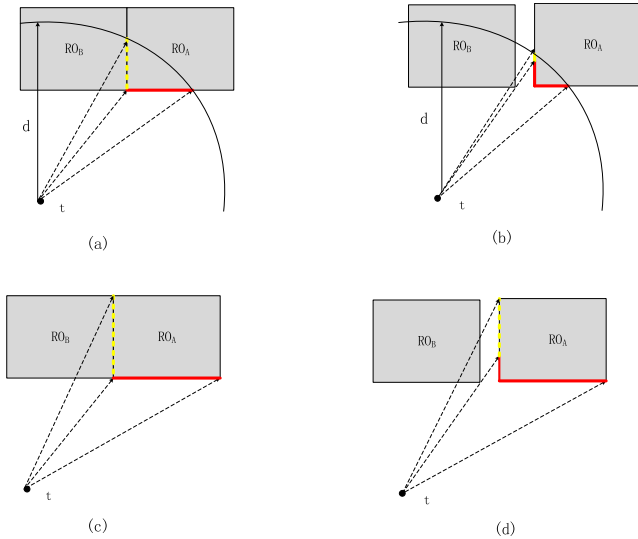
**Cognition Restriction:** The visible boundary should meet the Pareto principle, for which approximately 80% of effects originate from 20% of the cause, whether from a cognition or algorithm perspective. As shown in Figure 11, the space is divided into 8 cones, and each cone occupies  $45^\circ$ . The occupation angle of the portion of the visible boundary meets restriction 2 in that cone should be approximately  $9^\circ$ .

When there are two reference objects in a locality description and the angle between the two direction descriptions of the two reference objects is not equal to  $180^\circ$ , this is unacceptable from a positioning perspective because there are two locations. To solve this problem, a principle based on direction relations in the locality description is given as follows.

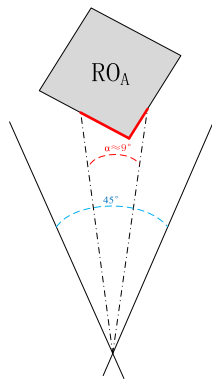
**Principle:** As illustrated in Figure 12, the space is divided into eight directions, and each direction is assigned numbers from 1 to 8 in a clockwise direction. The path<sub>(a)</sub> is the path between two direction lines. Take the locality description “my front 50 m is  $RO_A$ , and my right is  $RO_B$ ” as an example. Lines 1 and 3 respectively connect  $RO_A$  and  $RO_B$  to the positioning locality (i.e.,  $t_1$  and  $t_2$ ). The unique positioning locality should meet the requirement that the direction from front (1) to right (3) is clockwise, and path<sub>(a)</sub> = 2, that is,  $t_1$ .

When calculating the quantitative distance and relative direction of the positioning locality (i.e.,  $t$ ) to the visible

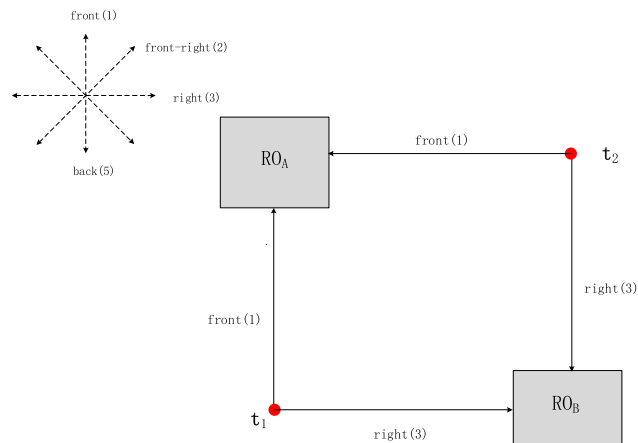




**FIGURE 10.** Illustration of visible boundary for a visible restriction (red line). The red solid (visible boundary) and yellow (invisible boundary) dashed lines form the boundary of the reference object ( $RO_A$ ) from locality  $t$ . The lines of sight are simulated by black dashed lines. (a) Visible boundary of quantitative distance interrupted by adjacent  $RO_B$ ; (b) visible boundary of quantitative distance interrupted by disjointed  $RO_B$ ; (c) visible boundary of qualitative distance interrupted by adjacent  $RO_B$ ; and (d) visible boundary of qualitative distance interrupted by disjointed  $RO_B$ .



**FIGURE 11.** Illustration of the Pareto principle.



**FIGURE 12.** Illustration of the Principle.

boundary, we should sample the visible boundary. However, some segments should be eliminated from visible restrictions

to cognition restrictions. To be consistent with cognition, we provide a sampling method (algorithm 1) as follows:

**Algorithm 1**

**Step 1:** Equally divide the angle between the positioning locality and the end points of the visible boundary. Obtaining the sampling points of the visible boundary meets the visible restriction.

**Step 2:** Sort the sampling points’ polar coordinates. Filter the sampling points with the recursive method. Two points (i.e., clockwise and anticlockwise) are eliminated until the cognition restriction is met.

**End for**

Here, we use the implicit locality description (i.e., “object A is 50 m in front, object B is (near) to the left, object C (near) is to the front-left”) as an example to illustrate the probability calculation process in the located region.

Without loss of generality and explaining our method clearly, we regard a polyline and polygon as a set of points, namely,  $A = \{a_1, a_2, \dots, a_n\}$ . A, B and C are ROs, and  $T = \text{Located\_Region}(A,B,C)$ . The  $\text{Visible\_Bdy}(A)$ ,  $\text{Visible\_Bdy}(B)$  and  $\text{Visible\_Bdy}(C)$  are the visible segments of A, B and C, respectively, that meet the restrictions. We let  $\text{dir}(A,t,B)$  denote the angle between  $t$  and two visible segments of A and B, and  $\text{dir}(t,A)$  denote the distance from  $t$  to  $\text{Visible\_Bdy}(A)$ . The other  $\text{dir}(A,t,C)$ ,  $\text{dir}(B,t,C)$ ,  $\text{dis}(t,B)$  and  $\text{dis}(t,C)$  are the same.

The process is as follows.

**Step 1:** Calculate the probability of relative direction in the located region;

$$P_{dir}^{rel}(t) = P_{dir}^{rel}(A, t, B)P_{dir}^{rel}(B, t, C)$$

where  $P_{dir}^{rel}(A, t, B)$  and  $P_{dir}^{rel}(B, t, C)$  are the membership degrees that map  $\text{dir}(A,t,B)$  and  $\text{dir}(B,t,C)$  via the relative direction membership functions in Equation (1) or (2).

**Step 2:** Calculate the probability of quantitative distance in the located region;

$$P_{dis}^{quan}(t) = P_{dis}^{quan}(t, A)$$

where  $P_{dis}^{quan}(t, A)$  is the membership degree that maps the  $\text{dis}(t,A)$  via the quantitative distance membership function Equation (3).

**Step 3:** Calculate the probability of qualitative distance (i.e., near) in the located region;

$$P_{dis}^{qual}(t) = P_{dis}^{qual}(t, B)P_{dis}^{qual}(t, C)$$

where  $P_{dis}^{qual}(t, B)$  and  $P_{dis}^{qual}(t, C)$  are the membership degrees that map the  $\text{dis}(t,B)$  and  $\text{dis}(t,C)$  via the qualitative distance membership function in Equation (4).

**Step 4:** Positioning;

$$P(t) = P_{dir}^{rel}(t)P_{dis}^{quan}(t)P_{dis}^{qual}(t)$$

The calculation process is based on a joint probability function according to the spatial relation clue in the locality

description. In other words, the process should be adjusted according to different spatial relation clues in the locality description.

## V. CASE STUDY

### A. PROCEDURE

The cognitive experiment is conducted in a shopping mall, which offers a sufficient number of participants. To better verify our experiment, two floors (F1 and F7) of the shopping mall within a 45 m visual space are selected as our experimental ground. All participants participate once. Their ages range from 15 to 54, and they have different backgrounds. Before the experiment, all participants are told to describe context.

Describe context: If you lost your family or friends, there is a phone that can translate your locality description into a locality, and your family or friends can find you easily. Please describe your locality with distance, direction or both.

### B. PARAMETERS

We adopt a 98% confidence interval as the  $\beta$  and  $\gamma$  of the quantitative distances (i.e., 10 m, 30 m, 50 m).  $\alpha$  and  $\delta$  can be obtained by their normal distribution. The upper and lower bounds of quantitative distances are not particularly critical but must not be too small or large. Bounds that are too small will not reflect the influence area, and bounds that are too large will increase the calculation complexity. Here, a 70% confidence interval is regarded as the upper and lower bounds of quantitative distances. The related parameters of other quantitative distances can be obtained by interpolation.

For relative direction, the range of parameter  $a$  is [2], [5] multiplied by path ( $\ominus$ ). The angles that meet the cognition restriction is  $10^\circ$  and  $20^\circ$  for the 8 and 4 relative direction models, respectively. Lacking additional contextual information, we cannot determine how many cones the participants potentially divide the space. However, the direction relation “left-front” inferred that the space was divided into 8 cones. Thus, without additional contextual information, we use a 4-cone relative direction membership function.

### C. EXPERIMENTAL RESULTS

We collected over 521 data, of which 361 data met the positioning requirement. Then, the related data were divided into explicit and implicit locality descriptions, as provided in Section 4.1. For convenience, Explicitly-Scene2 and Explicitly-Scene3 respectively denote the two and three reference objects in the explicit locality description. Implicitly-Scene2-1 denotes that there are two reference objects in the implicit locality description, and there is one reference object that lacks quantitative distance. As shown in Figure 14, the related data are marked as points. The collected locality description is shown in Table 3.

From the marked point in Figure 14 the locality description including quantitative distance (i.e., Explicitly-Scene2, Explicitly-Scene3, Implicitly-Scene2-1, Implicitly-Scene3-1, and Implicitly-Scene3-2) appears to be in a relatively

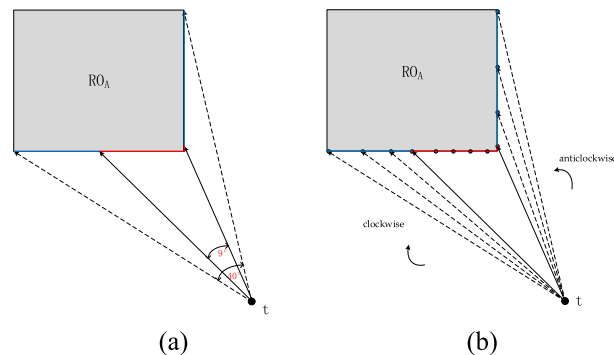


FIGURE 13. Illustration of cognition restriction and the sampling method. (a) Cognition restriction; (b) sampling method.

spacious place, where there is a lot of space for participants to make distance judgements. However, the distribution of locality descriptions without quantitative distances (i.e., Implicitly-Scene2-2 and Implicitly-Scene3-3) is uniform. In general, the locality description for the space where there are enough reference objects and the distribution of explicit and implicit locality descriptions confirm human spatial cognition.

Figures 15 and 16 respectively show the positioning results for Implicitly-Scene3-1 in F1 and Implicitly-Scene3-3 in F7. The locality descriptions are “front 15 m is TISSOT, left 15 m is ZuoKY, left-front is I DO” and “front is FuCQ, right is RongLiJ, left-front is KeDuoCS”. Darker colour correspond to greater probability. The red point represents the positioning locality, i.e., the maximum probability point or the center point of the maximum probability region. The blue point denotes the participants’ standing locations. From the results, the red point relative to the reference objects in the locality description is consist with the relative direction description.

To verify the positioning accuracy, the positioning curve and empirical cumulative distribution functions (CDFs) of the 7 scenes are illustrated in Figure 17. The positioning error is the distance from the maximum probability point or the center point of the maximum probability region to the participant locality (i.e., marked point). Table 6 shows the error statistics of the explicit and implicit locality descriptions. As shown in Figure 18, considering qualitative distance (i.e., near) in an implicit locality description, the positioning accuracy is improved, which reflects that participants potential selected nearby reference objects. The positioning accuracies are respectively improved by 0.54 m, 1.18 m, 0.70 m, 0.84 m and 1.08 m for Implicitly-Scene2-1, Implicitly-Scene2-2, Implicitly-Scene3-1, Implicitly-Scene3-2, Implicitly-Scene3-3 (Table 4). The positioning accuracies of Implicitly-Scene2-2 and Implicitly-Scene3-3 showed obviously better improvements than the other three scenes because the quantitative distances of reference objects are not all equipped. In general, considering qualitative distance (i.e., near), the positioning accuracy is improved by 0.85 m.

Uncertainty is the intrinsic characteristic of spatial cognition and is inevitable. The large positioning error comes



FIGURE 14. Illustration of participant localities. (a) 1F, (b) 7F.



FIGURE 15. Positioning result for Implicitly-Scene3-1 in F1: “front 15 m is TISSOT, left 15 m is ZuokY, left-front is I DO. The participant is approximately 16.5 m away from TISSOT. (a) Global, (b) Local.

from unclear cognition and might be summarized as follows: First, via unclear quantitative distance cognition. The quantitative distance description of the reference object (RO) is too small or large (Figure 19). As shown in Figure 19, the quantitative distance description of the RO<sub>2</sub> participant standing at TO<sub>1</sub> is 15 m but is actually 8 m. Second, via

unclear direction cognition. Participants standing in adjacent positions have the same reference objects but different direction relation descriptions. As shown in Figure 19, a participant standing at TO<sub>1</sub> describes his locality as “front is RO<sub>2</sub>, left is RO<sub>3</sub>”, but another participant standing at TO<sub>2</sub> adjacent to TO<sub>1</sub> describes his locality as “right-front is RO<sub>2</sub>,

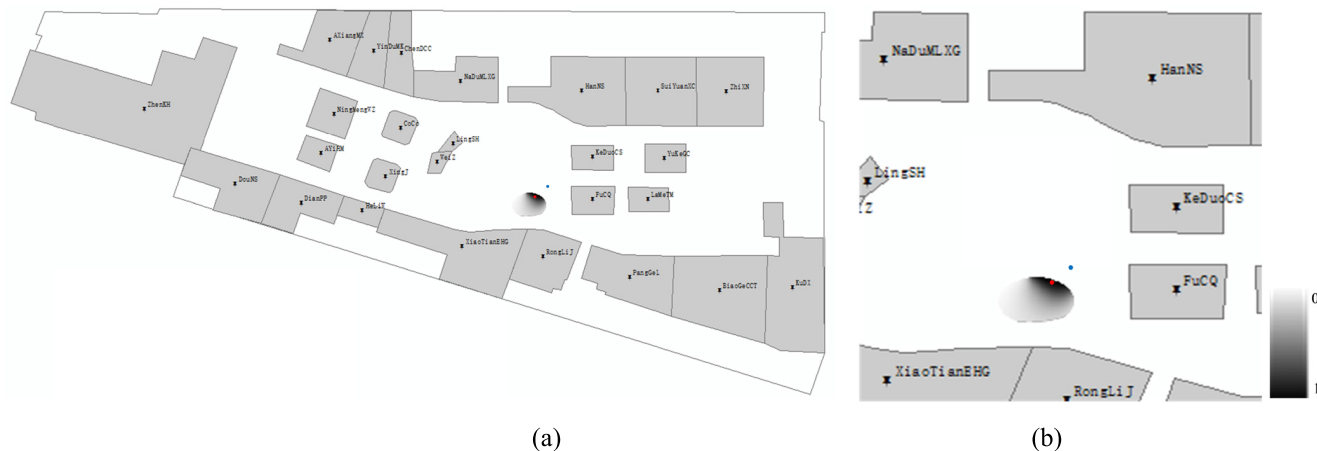


FIGURE 16. Positioning result for Implicitly-Scene3-3 in F7: “front is FuCQ, right is RongLiJ, left-front is KeDuoCS”. (a) Global, (b) Local.

TABLE 3. Locality description of Explicitly-Scene2 and Explicitly-Scene3.

Scene	RO1			RO2			RO3		
	Name	Direction	Distance (m)	Name	Direction	Distance (m)	Name	Direction	Distance (m)
Explicitly-Scene2	RongLiJ	right-front	15	FuCQ	left-front	10			
	FuCQ	Front	5	PangGeL	back	5			
	.....								
Explicitly-Scene3	HanNS	Left-front	20	FuCQ	right-front	20	KeDuoCS	Front	10
	FuCQ	Right-front	10	LaMeTW	Right	5	PangGl	Left	5
	.....								

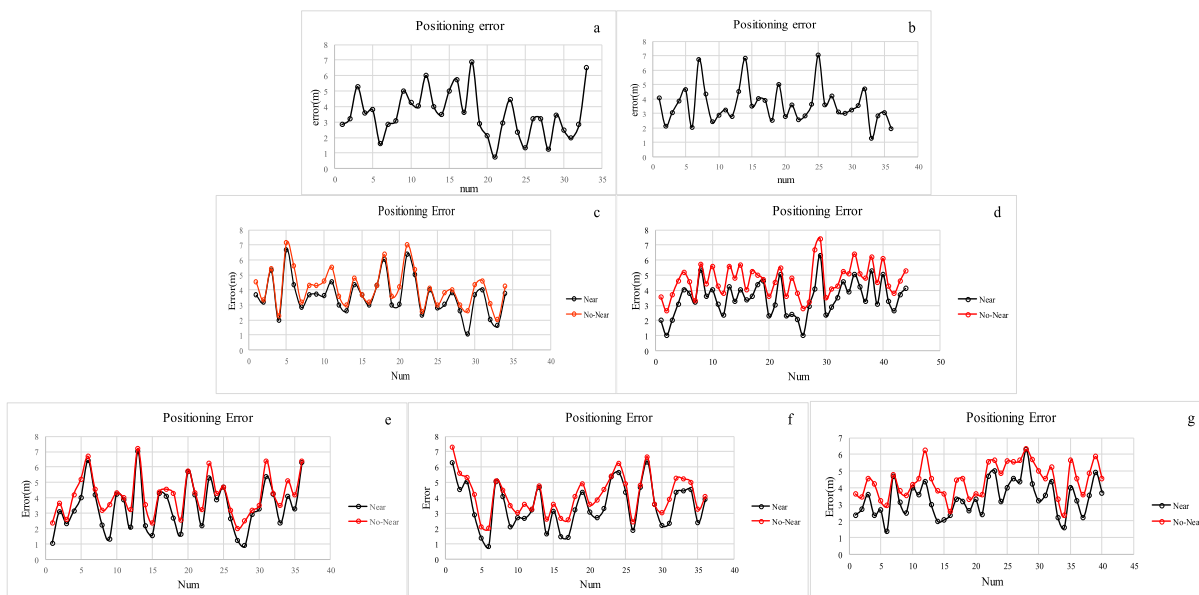


FIGURE 17. The positioning errors: the black and red lines respectively indicate positioning error considering qualitative distance (i.e., near) or not. (a) and (b) are for Explicitly-Scene2 and Explicitly-Scene3; (c), (d), (e), (f) and (g) are for Implicitly-Scene2-1, Implicitly-Scene2-2, Implicitly-Scene3-1, Implicitly-Scene3-2, and Implicitly-Scene3-3.

left-front is RO<sub>3</sub>”. The angles of reference objects in the locality descriptions are different (the former is 90°, the latter is 45°). This may result from the different orientations

associated with coming or standing (Figure 19). Third, via qualitative distance. The reference object that lacks a quantitative distance description is obviously farther away than

TABLE 4. Comparison of positioning error statistics for explicit and implicit scenes.

(a)

Scenes	Number	Maximum Error(m)	Minimum Error(m)	Mean Error(m)	90% accuracy
Explicitly-Scene2	33	6.50	0.75	3.48	5.68
Explicitly-Scene3	36	7.06	1.29	3.60	5.01

(b)

Scenes	Not Considering qualitative distance			Considering qualitative distance			
	Maximum Error(m)	Minimum Error(m)	Mean Error(m)	Maximum Error(m)	Minimum Error(m)	Mean Error(m)	90% accuracy
Implicitly-Scene2-1	7.14	2.03	4.15	6.70	1.05	3.61	5.32
Implicitly-Scene2-2	7.4	2.64	4.67	6.32	1.03	3.49	5.02
Implicitly-Scene3-1	7.21	2.01	4.15	7.02	0.91	3.45	5.64
Implicitly-Scene3-2	7.3	2.01	4.33	6.35	0.82	3.49	5.34
Implicitly-Scene3-3	6.33	2.36	4.44	6.28	1.38	3.36	4.69

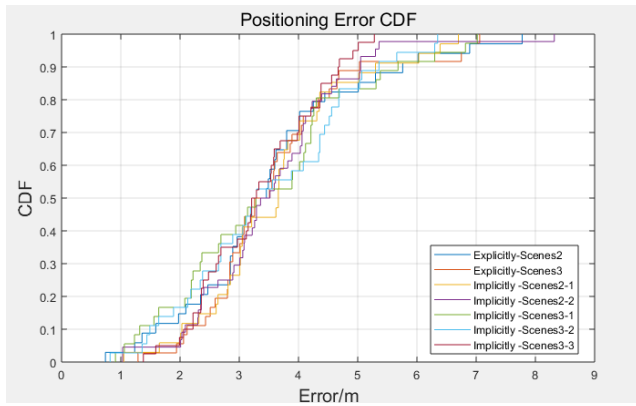


FIGURE 18. The empirical cumulative distribution functions (CDFs) for different scenes considering qualitative distance.

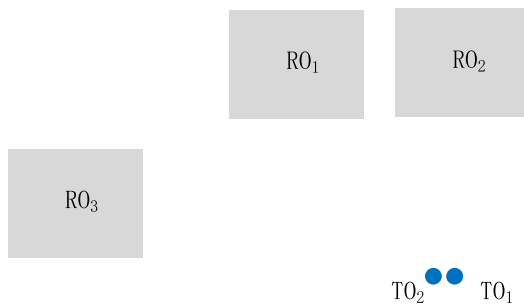


FIGURE 19. Illustration of unclear cognition. The red points represent the locations at which participants stand.

the reference objects that surround the participants. This may result from personal preferences or the fact that it is blocked by obstacles (e.g., concrete columns). As shown in Figure 19, the locality description for a participant standing at TO<sub>1</sub> is “front 15 m is RO<sub>2</sub>, left is RO<sub>3</sub>”. However, RO<sub>3</sub> is further than RO<sub>1</sub> from TO<sub>1</sub>. Additionally, large positioning errors may result from the combined addition of unclear distance (quantitative or qualitative) and direction cognition.

The positioning errors are grouped by the number of reference objects in the locality descriptions, and positioning

TABLE 5. Comparison of positioning errors with two and three ROs statistics.

Number of RO	Maximum Error(m)	Minimum Error(m)	Mean Error(m)
Two	6.50	0.75	3.48
Three	7.06	1.29	3.60

error statistics are shown in Table 5. The positioning errors for locality descriptions with two and three reference objects are almost the same, which reflects that more reference objects in a locality description do not contribute to improving positioning accuracy.

Figure 20 shows the overall positioning accuracy and empirical cumulative distribution function (CDF). The maximum and minimum positioning errors are 7.06 m and 0.74 m, respectively, and the mean positioning error is 3.50 m when using spatial relations in locality descriptions. The 35.15% and 87.46% accuracies are respectively 3 m and 5 m. Compared to current costly and complex indoor positioning technologies whose positioning accuracies are 3-5 m based on common smartphones, our positioning method is economical and its accuracy is acceptable. Additionally, if other data are considered, such as indoor roads and escalators, such data can generate spatial constraints on the positions of participants and improve the positioning accuracy to some extent.

VI. CONCLUSIONS AND FUTURE WORK

Spatial relations in locality descriptions convey locality clues and can support positioning. After a great deal of analyses (cognition, expression and computation), locality descriptions are divided into two categories (i.e., explicit and implicit) and are then subdivided according to the number of ROs. Based on this assumption, this paper presents a two-stage computational method for indoor positioning with spatial relations extracted from indoor locality descriptions. The first stage focuses on the located region, which is obtained via the intersection of quantitative or qualitative distances in explicit or implicit locality descriptions. The second stage

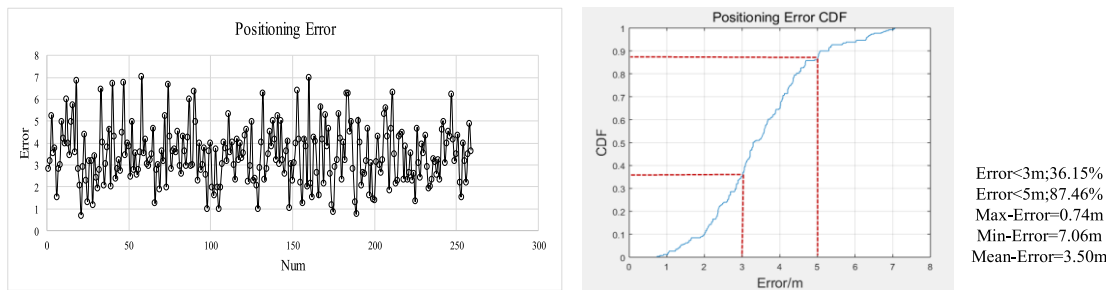


FIGURE 20. The overall positioning accuracy and empirical cumulative distribution function (CDF).

aims to describe the probability distribution in the located region, which is a joint probability function consisting of direction and distance (quantitative and qualitative distances) membership functions. Additionally, from the computational and cognition perspectives, some restrictions are provided. The study achieves a positioning accuracy of 3.50 m.

The contributions of this paper are apparent from three perspectives. From the perspective of modelling, this paper proposes a modelling method for relative direction, quantitative distance and qualitative distance based on cognition and geometry computations. From the perspective of methodology, this work presents a two-stage computational method that includes obtaining a located region and describing a probability distribution in that region. As indicated by the experiment results, the method has an acceptable performance in indoor positioning compared to using traditional indoor positioning technology. From the perspective of application, this paper presents an innovative use of spatial relations extracted from locality descriptions for indoor positioning.

The proposed approach for indoor positioning with spatial relations has limitations and can be improved by future work. First, the classification scheme of indoor locality descriptions provided in the paper serves as an example of the complexity of locality descriptions and is not considered to be a final scheme. Second, the qualitative distance (i.e., near) is based on the assumption all weights of ROs are the same. If the weights of all ROs differ, the ability of multiplicatively weighted Voronoi diagrams to answer the multiplicatively weighted near relation is worth being discussed. Third, it is undeniable that there are other kinds of ROs in locality descriptions, such as escalators and pillars, which can narrow the located region to improve positioning accuracy. Future researches should model these ROs and their related spatial relations.

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