FUZZY POSITIONING MODELING OF NATURAL LANGUAGE LOCATION DESCRIPTION

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Commission VI, WG VI/4

KEY WORDS: Uncertainty, Spatial relationships, Fuzzy sets, Membership function, Positioning locations, Natural language

ABSTRACT:

The development of cognitive technology and natural language understanding has made the interaction between humans and machines more mature. Natural language interactive location services through language or text are more in line with human cognitive habits, and it is the future development direction of location service techniques. Different from accurate GPS location, the uncertainty of human cognition causes the natural language position description is of uncertainty. How to take the uncertainty of position description into account to model it, and further establish a positioning computing framework that supports the expression of uncertainty, is a difficult problem in this field. At present, quantitative spatial relationship models can be well applied to navigation and positioning. However, these models cannot be directly transferred to deal with qualitative spatial relationships, such as positioning based on natural language descriptions. An effective solution is to establish a method to transform the qualitative natural language positioning into a quantitative one. To build this transformation, we proposed a fuzzy positioning model based on fussy mathematics theory and methods. The proposed model was validated using indoor and outdoor positioning experiments. The experiments showed that it could achieve a high positioning accuracy both indoor and outdoor.

1. INTRODUCTION

Positioning with natural language description is a topic of next-generation GIS (Jiang,2006). The resolution of positioning with reference objects (RO) and spatial relations descriptions would take us closer to human-like geographic services that communicate with people intelligently about their everyday spatial needs (Vasardani,2003). Uncertainty is the inherent characteristic of geographic information (Gong 2012). Localities description has numerous sources of uncertainty, external or internal factors, such as personal cognition with distance and spatial distribution affection.

Generally, the uncertainty of position description mainly manifests in the uncertainty of the reference object, the spatial relation, and the target object. The uncertainty of the reference object contains the uncertainty of its name spatial position, such as "Northern China". Montello (2003, 2014) believed that the fuzziness of reference objects is not only caused by "logical ambiguity" or "cognitive error", but also is real fuzziness.

The orientation relation refers to the position of a reference object relative to the target object. Due to the fuzziness of the reference object (or the target object) and the difference of orientation cognition, there is inevitable uncertainty of orientation relation description. In daily expression, people are more likely to use qualitative orientation relation. For example, people say, "I am at the northeast of Hongshan Square" rather than "I'm at 45 degrees of Hongshan Square".

Distance relation refers to the distance between reference objects, and it can be divided into a qualitative distance and quantitative distance according to whether qualitative values denote the distance or not. The description of distance is usually fuzzy due to recording accuracy, measurement error, and distance cognition. For example, the description of “I am 100 meters east of the south gate of Wuhan University” does not mean the distance between the speaker and the south gate is accurate 100 m. Qualitative distance refers to the none numeric distance description. Such a description is fuzzier than the above semi-quantitative distance description; however, it is more widely used in daily life. Yao (2005) analyzed people’s understanding of qualitative distance while driving. In this paper, the proposed method considers the influence of people’s educational background, family background, age, gender, etc., on people’s cognition. Yao used Ordinal Logit Regression to map the quantitative distance to qualitative distance, including “very near”, “near”, “not-so-near-yet-not-so-far”, “far”, and “very far”, and accomplished traffic inquiry system based on qualitative distance.

Aiming at solving the uncertainty of position description includes the uncertainty of orientation relation, many studies proposed various practical methods of spatial positioning.

Wieczorek (2004) proposed to use a point-radius method to locate the museum species and applied it to explore the species diversity. The point-radius method uses a point to represent the location of the target object and uses the radius to represent the uncertainty in the position description. The positioning process includes the following steps. (1) Determine the target object's location according to the address library, map, etc. (2) Calculate the uncertainty of the location of various sources, including the reference object, spatial relation, projection relation, coordinate precision, and map scale. (3) Taking all of the uncertainty into consideration, and utilize the error propagation to integrate the uncertainties and determine the radius.

The point-radius method is easy to use since the uncertainty can be expressed by an attribute independent with the geographical position. However, there are some limitations. First, it uses point to represent the target object, which neglects the actual shape and size. Second, it uses a circle of a certain radius to represent the uncertainty of the position description, which assumes the distribution of the uncertainty is uniform in a different direction. This cannot fully consider the distribution regularities of the uncertainty, and it is inclined to overestimate the uncertainty to cover all possible areas as much as possible.

In response to the problems of the point-radius method, Guo et al. (2008) proposed a position description method based on probability. The PDF method can fill the region of uncertainty with a probability value and uses these probability values to generate an estimated shape, which takes into account the shape and size of the target object. In addition, the PDF method can fully consider the distribution regularity of the uncertainty from all directions and distances. Compared with the point-radius method, which considers the uncertainty into an even distribution circle, the uncertainty can be demonstrated more accurately.

The advantages of the PDF method make it widely used and extended. What Liu et al. (2009) proposed is a conceptual model, and specific applications can use this framework and choose the source of uncertainty flexibly according to the actual situation. Doherty et al. (2011) applied this model into the emergency rescue at Yosemite national park and compared point-radius with PDF method. The results confirmed that the PDF showed superior performance than the point-radius method.

To sum up, the application of spatial relation in position description mainly focuses on the research of small scale, including specifies diversity and emergency rescue. There is rarely research studying the locations in indoor environments, such as mall location and pedestrian location navigation, or studying the locations in large-scale outdoor environments such as Ride-hailing applications.

The paper intends to regard spatial objects, spatial relationships, and positioning results as fuzzy variables. Fuzzy set theory (ZadehL, 1965) is used to construct its membership function. PDF method and its extension are used to calculate the possible membership (joint probability) of the allowable area. The net point or area with the biggest probability is finally recommended as the target point or area. The paper studies the location cases of indoor shopping malls and outdoor subway stations and analyzes the positioning accuracy of the experiments to verify the effectiveness of the method.

2. METHODS

2.1 Uncertainty modeling of qualitative position description based on Fuzzy set Theory

Zadeh (1965) proposed the Fuzzy set theory in 1965. In the following decades, the Fuzzy set theory has been continuously developed and improved and has been successfully applied in the field of geospatial (Burrough, 1996).

Classical set theory has two most basic properties: elements are different from each other, and the boundaries of the range are clear. The relationship between an element x and the set A, either x belongs to A, or x does not belong to A, and only one assertion is true. In real life, many things are not "otherwise", for example, "far" and "near" are all vague concepts. Therefore, the basic idea of fuzzy sets is to expand on the concept of classic sets and expand binary functions into continuous functions. In the classic set, the degree of membership of an element can only take 0 or 1, while in the fuzzy set, the degree of membership of an element can take any value in the interval [0,1]. The value represents the degree to which the elements belong to the set. The mapping of all elements in the universe to their membership values constitutes the membership function (MF).

In the fuzzy set representation of spatial relationships, the membership function describes the degree in which each point in the space (usually a two-dimensional space) belongs to a fuzzy geographic element or spatial relationship. So, its membership function is two-dimensional, which can be expressed as $z = f(x, y)$, where z represents the value of membership at the point (x, y). This two-dimensional membership function can be visually represented by a GIS raster map.

In this paper, we regard the reference objects, spatial relationships and target objects in the natural language position description as fuzzy variables, and use fuzzy set theory to establish their membership function to express their uncertain characteristics through the cognition experiments, etc.

2.2 The establishment of fuzzy model of spatial relations descriptions

The core of fuzzy modeling is to construct the fuzzy sets and their membership functions for all qualitative spatial relations involved in natural language location descriptions. In this paper, only the distance and orientation relations commonly used in the natural language locating desciptions will be studied.

Several methods can be used for determining membership functions, include (1) fuzzy statistics (2) assignment methods, (3) borrowing existing objective scales, (4) cognitive experiments. We will use cognitive experiments to build member functions for both the qualitative distance and qualitative orientation relations involved in natural language descriptions.

Here, firstly, the fuzzy modelling of qualitative distance will be conducted by means of the recngnition experiments. A Shopping Market, will be chosen as the first indoor experiment site. It is not only an ideal indoor environment but also provides us enough samples of varying ages. We design the cognition distance into three groups, i.e., 10m, 30m, 50m, of which contains 40 experiment samples, and each of them is sampled once, avoiding affection between different groups. All the distance samples in each group as a whole are confirmed to obey the normal distribution. From the experiments, we conclude that the further the cognitive distance is, the larger deviation compared to the right distance is. Trapezoid function offers many advantages to define fuzzy distance relations, such as computation efficiency, robustness, and intuitive (Vanegas 2011). Many qualitative and semi-qualitative distance relationships are defined with trapezoid function (Gong 2012, Liu 2009, Vanegas 2011). Figure 5 shows the probability distribution of the qualitative distance and the extracted trapezoid membership function. Let α, β, γ, δ be a non-negative number, $\alpha \leq \beta \leq \gamma \leq \delta$. Based on the cognitive experiment, we model the fuzzy distance as a nonisosceles trapezoid membership function as Equation (1), among it, β and γ are the deviations from the right distance, α and δ may be derived from fuzzy distance distribution of our experiment samples.

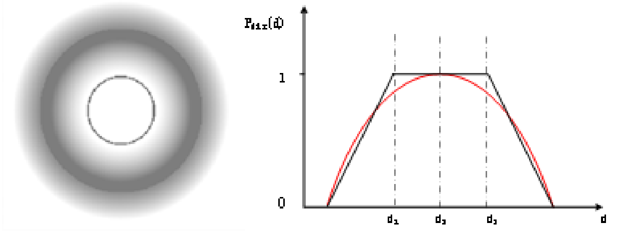

Figure 1 Uncertainty representation of semi-qualitative distance.

$$\mu_{\mathrm{dis}}(d)=\begin{cases}1 & \beta \le d \le \gamma \\ (\beta-\alpha)(d-\alpha) & \alpha \le d \le \beta \\ (\gamma-\delta)(d-\delta) & \gamma \le d \le \delta \\ 0 & d \le \alpha, \delta \le d\end{cases} \qquad (1)$$

There is ambiguity in the human cognition of space, so it is difficult to describe the orientation during the calculation process accurately. Krishnapuram (1993) believes that people's cognition of the orientation relationship of space objects has a great relationship with the angle. For instance, one would search a cone area approximately 45° turning from front to front-left, which has nothing to do with distance. Accordingly, trapezoidal membership functions such as "above, below, between" are defined to describe the mutual relations between space objects.

The trapezoid membership function is not only intuitive, but also robust and easy to calculate (Schockaert 2008). The closer the reference object is to the center line of sight, the closer it is to the described orientation (Hardiess 2015). As shown in Figure 2c, when the target is at point b, its membership in the north direction is small. When it reaches point a, that is, near the center line of sight, the closer the target is to the true north direction, the greater the membership degree.

Figure 2a shows the orientation of 8-direction mode and 4-direction mode; we define the function for qualitative relative Equation (2) show nonisosceles trapezoid membership function of the orientation of 8-direction mode. In 8-direction mode, the visual field of “RO” is divided into eight sectors, namely, “front, back, left, right, right front, right back, left front, and left back” or “north, south, west, east, northeast, northwest, southwest, and southeast”.

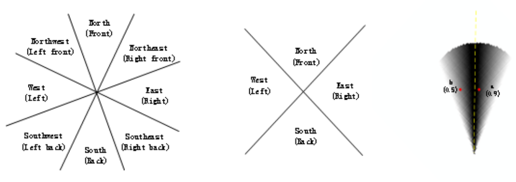

Figure 2. (a) 8 orientation model; (b) 4 orientation model;

$$\mu_{\mathrm{reldir}}(\Theta)=\begin{cases}1 & \left|\frac{\pi}{4}\times \mathrm{path}_{(\Theta)}-\Theta\right| \le a \\ \dfrac{\frac{\pi}{8}+\left|\frac{\pi}{4}\times \mathrm{path}_{(\Theta)}-\Theta\right|}{\frac{\pi}{8}-a} & a \le \left|\frac{\pi}{4}\times \mathrm{path}_{(\Theta)}-\Theta\right| \le \frac{\pi}{8} \\ 0 & \left|\frac{\pi}{4}\times \mathrm{path}_{(\Theta)}-\Theta\right| \ge \frac{\pi}{8}\end{cases} \qquad (2)$$

2.3 The calculation of joint membership functions of qualitative location in descriptions

The location can be regarded as an admissible area, which is determined by the constraints of the spatial relationships involved in its descriptions. Therefore, the location’s membership function, called the joint membership functions, can be derived from all the spatial relations’ membership functions. Here is the calculation schema for the joint membership functions.

Given that the location description contains two or many ROs associate with their spatial relations. All the distance and orientation relationships involved in the description are respectively noted as D1(r, c), ..., Dp (r, c), and O1(r, c),..., Oq (r, c). Among them, p and q are the distance and orientation relation numbers.

(1) The admissible area of the target position based on the description is calculated. This step will use the quantitative spatial analysis methods that include Voronoi methods to limit the admissible area in combination with the referenced objects and etc.

(2) The admissible area is rasterized into a grid with row rnum and column cnum, and both the membership value D(r, c) and O(r, c) of each cell grid(r, c) is calculated respectively. Since the membership function of spatial distance is established, and the area of a cell is known as area A too, and the distance membership value D (r, c) of the cell grid (r, c) can be obtained by calculating the integral of D (x, y) over area A. A similar method can be used to obtain the orientation membership value O (r, c) of the cell Grid(r, c).

(3) The joint membership value J(r, c) is calculated by combining both the distance and orientation membership value of each cell Grid(r, c). Here, we have J(r, c)=D1(r, c)*..., Dp(r, C)* O1(r, c)*..., Oq(r, C).

(4) The cell Grid(r, c) with the highest membership value is recommended as the target location, and meanwhile, the joint membership values of all grid cells of the admissible area are visualized with a shaded polygon.

3. EXPERIMENTS AND RESULTS

3.1 INDOOR POSITIONING LOCALITIES BASED ON SPATIAL RELATIONSHIP: DISTANCE AND DIRECTION

In order to discuss the accuracy of positioning using the qualitative distance and relative orientation in the position description, we conducted a cognitive experiment for two positioning scenarios, respectively, with two ROs and three ROs. Scenarios 1: Positioning with two ROs. Its location description is “front 20m is TISSOT, and left 15 m is ZuoKY”. Scenarios 2: Positioning with three ROs. Its location description is ‘front 20m is Watch, left-front 30m is Playboy, left 30m is ZuoKY’.

The two experiments were conducted in an indoor mall with a viewing distance of 45m. We selected two places with good visibility in the room, labeled TO (A) and TO (B), randomly selected the subjects in the mall, and let the subjects stand around the pre-marked points and look around. Qualitative distance and orientation describe their location, and the experimenter records these distance and orientation description information. The subjects were between 20 and 60 years old and had different educational backgrounds, including men and women.

Based on the cognitive experiment results of quantitative distance, we choose a 98% confidence interval as the upper and lower boundaries (β and γ) of the quantitative distance membership function value of 1, namely 10m (β = 9.1, γ = 12.2), 30m (β = 27.8, γ = 38), 50m (β = 49.5, γ = 59.7), the values of α and δ can be obtained directly from the experimental results, and 15 m (α = 5.5, β = 13, γ = 18, δ = 33.6) and 20 m (α = 7.4, β = 16, γ = 25, δ = 45.6) can be obtained by interpolation. The 86% confidence interval is selected as the upper and lower boundaries of the fuzzy boundary.

When the description of the orientation relationship lacks semantic information, it is impossible to determine the potential consciousness of the position descriptor to divide the space into several areas. For example, we cannot determine whether the orientation relationship "front" should use the 4-direction relationship model or the 8-direction relationship model; but "left front" represents the 8-direction relationship model. For this reason, when semantic information is lacking, we use the 4-direction relationship model for calculation. The value of a in the relative orientation membership function is the product of [2,5] and path (Θ). The angle of the visible line segment, satisfying the visual constraints (Pareto principle) is 10 °(8-orientation relationship) or 20 °(4-orientation relationship). To verify the positional accuracy with the model, two group positioning experiments, with two ROs and three ROs, are conducted. Different people have different angles between two orientation descriptions for the same scene.

Figure 3 shows the results of the calculation of Scenario 2. The left part of the admissible domain, deeper color, is the point with the higher probability, which meets the spatial relationship (i.e., distance and orientation) from spatial cognition.

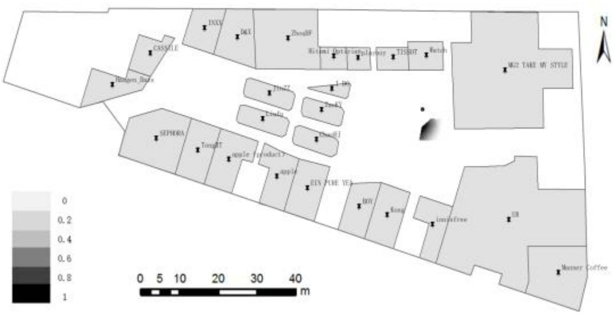

Figure 3. Positioning of location description with three ROs

In order to discuss the positioning accuracy, we did a number of experiments on the pre-marked points TO (A) and TO (B), and plotted the positioning error curve (Figure 4). The positioning error is determined by calculating the distance between the point with the highest probability and the marked point.

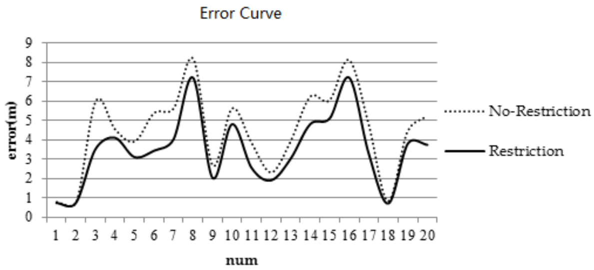

Figure 4 positioning error curve

Through statistics, it is found that with a natural understanding of the complex indoor environment, the positioning accuracy of 3.5m can be achieved by relying on the relative orientation and the fixed distance.

3.2 OUTDOOR POSITIONING LOCALITIES BASED ON SPATIAL RELATIONSHIP: DISTANCE AND DIRECTION

Taking the subway stations as reference objects, we confine the natural language position description as “20m front (or north) of K exit of Guangbutun MTR station”. For example, in Figure 4, the point 1 (114.362666, 30.52505) is the position located by mobile phone, the point 2 (114.362703, 30.52473135) is the revised location, and the point 3 (114.362784, 30.524727) is the position located by GPSMAP. It is noted that the location error of the revised result is smaller than the location result of the mobile phone, and it corrected the error of wrongly locating the position on the other side of the road.

Figure 5. The distribution of the positions located by different methods. The point 1 is the position located by mobile phone, the point 2 is the paper-revised location, and the point 3 is the position located by GPSMAP.

According to the method proposed in this paper, for the collected data, we paper-revised the location results of mobile phones according to the position description of passengers. After obtaining the paper-revised location results, we calculated the location error before and after the revision.

It was found that the average location error of the location results of the mobile phone was 144 m. After revising the location results using the auxiliary positioning method based on the passenger position description about the directional and quantitative distance relation, the average error of the paper-revised location results decreased to 18.5 m, and the average location accuracy increased 125.5 m. When the mobile phone used high precision (GPS) positioning mode, the average location error was 18.8 m, the average error, after paper-revised, was 23.4 m, and the accuracy decreased 4.6 m. Figure 6 and Figure 7 demonstrate the error curve of the location results of the mobile phone and the paper-revised results under different modes. The dotted line and solid line represent the error curve of the location results of the mobile phone and the paper-revised results, respectively.

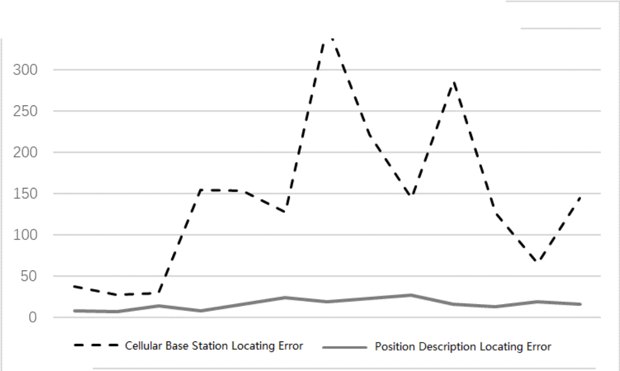

Figure 6. The error curve of the location of mobile base stations and the paper-revised results, represented by dotted line and solid line, respectively.

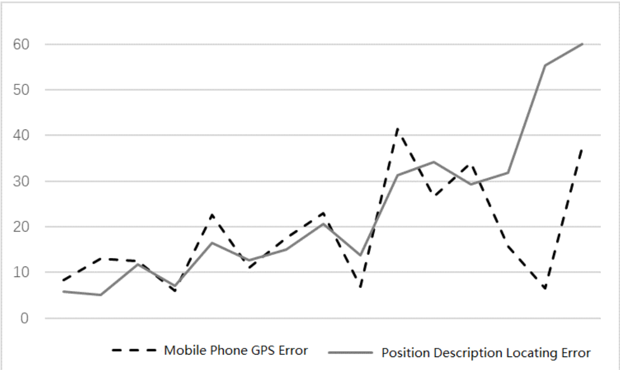

Figure 7. The error curve of the location of GPS and the paper-revised results, represented by dotted line and solid line, respectively.

Figures 6 and 7 show that when the mobile phone uses base station positioning mode, the auxiliary positioning method based on position description can significantly improve the location accuracy, and the average location error was 18.5 m. When the mobile phone uses GPS positioning mode, the location accuracy of the auxiliary positioning method based on position description was lower than the GPS results, with the location error was 23.4 m and 18.8 m, respectively, and the accuracy decreased 4.6 m. These results illustrated that the proposed auxiliary positioning method based on position description is adaptive for the situation with severe environment shielding, and the GPS is unavailable, the proposed method can significantly improve the location accuracy.

4. CONCLUSIONS

This paper proposes a fuzzy localization model of natural language description, which uses fuzzy sets and fuzzy member functions to represent the qualitative location and spatial relationships. Among them, both the fuzzy member function of qualitative distance and orientation are represented by two isosceles trapezoidal functions, and their trapezoid parameters are obtained through cognitive experiments. Further, the qualitative spatial position is represented by the admissible region, which is as well regarded as a fuzzy set with its fuzzy member function to depict its admissible probability. Since the area is determined by all the constraints of all the qualitative spatial relationships involved in its description, its member function can be derived by integrated or join together all the member functions of all the involved spatial relations, which is called the joint member function. Experiments of indoor positioning are conducted to validate the effectiveness of the proposed method. The total indoor positioning accuracy of the experiment reached 3.5m and outdoor positioning accuracy of the experiment reached 18.5m.

In terms of positioning with natural language descriptions, some issues still need to be further researched in future: As one of the qualitative distance descriptions, “near” and “far” are also high-frequency vocabularies in our daily life communication. Besides, more topology relations need to be discussed too. Taking them into consideration will make the positioning of locations more complete.

ACKNOWLEDGEMENTS

This research was supported by the National Natural Science Foundation of China (Grant No. 41471323).

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