The work is devoted to the problem of interpretation of fuzzy semantics of cognitive descriptions of spatial relations in natural language and their visualization in a geographic information system (GIS). The solution to the problem of determining the fuzzy spatial location of an object based on vague descriptions of the observer in natural language is considered. The task is relevant in critical situations when there is no way to report the exact coordinates of the observed object, except by describing its location relative to the observer itself. Such a situation may be the result of a crime, terrorist act or natural disaster. An observer who finds itself at the scene transmits a text message, which is a description of the location of the object or place (for example, the crime scene, the location of dangerous objects, the crash site). The semantics of the spatial location of the object can be further extracted from the text message.

The proposed fuzzy approach is based on the formalization of the observer's phrases, with which it can describe spatial relations, in the form of a set of linguistic variables that determine the direction and distance to the object. Examples of membership functions for linguistic variables are given.

The spatial knowledge base is built on the basis of the phrases of observers and their corresponding fuzzy regions. Algorithms for constructing cognitive regions in GIS have been developed. Methods of their superposition to obtain the final fuzzy location of the object are proposed. An example of the implementation of a fuzzy model for identifying cognitive regions based on vague descriptions of several observers, performed using developed Python scripts integrated into ArcGIS 10.5, is considered

Keywords: cognitive description of spatial relationships, spatial modeling, fuzzy logic, geographic information system

UDC 004.021:004.81
DOI: 10.15587/1729-4061.2021.246556

A FUZZY APPROACH FOR DETERMINING THE COGNITIVE SPATIAL LOCATION OF AN OBJECT IN GEOGRAPHICAL INFORMATION SYSTEM

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Received date 04.11.2021
Accepted date 04.12.2021
Published date 29.12.2021

***How to Cite**: Kuznichenko, S., Buchynska, I. (2021). A fuzzy approach for determining the cognitive spatial location of an object in geographical information system. Eastern-European Journal of Enterprise Technologies, 6 (9 (114)), 24–31. doi: https://doi.org/10.15587/1729-4061.2021.246556*

1. Introduction

Geographic information systems (GIS) are widely used in various spheres of human activity. GIS offers sophisticated functions for the analysis and modeling of spatial data, while operating with clear coordinates, directions and areas, represented as points, lines and polygons [1]. The mathematical apparatus for working with graphic primitives is well studied and developed.

However, more and more researchers' attention is focused on the processing of fuzzy information, through which the geographical position of objects and their spatial relationships can be described [2–5]. Models and methods of multicriteria decision-making integrated into GIS are often based on the processing of subjective and fuzzy information [6, 7]. In addition, the very concept of a geographical location is increasingly viewed as a product of human thinking, derived from spatial experience and used to describe a part of Cartesian space [8, 9].

The location is usually determined by the user in natural language using various cognitive coordinate systems [10]. Language can structure space through "linguistic space", making it easier to interpret spatial relationships between objects [11]. In everyday life, people are more likely to operate with subjective judgments, describing the location of objects based on a cognitive understanding of geographic space. Therefore, it is important that GIS can represent and analyze cognitive spatial information, formalize topological and geometric reasoning with indefinite objects, in order to satisfy the requirements for personalized systems.

The increase in the volume of text messages exchanged by Internet users on social networks and instant messengers is facilitating the collection of big data to extract the semantics of spatial location. The implementation of this process is possible through the use of a natural language processor and artificial intelligence methods [12, 13]. In this regard, the problem of determining the location of a spatial object in a GIS based on the verbal description of observers is of interest. This task can be relevant in critical situations when it is not possible to communicate the exact coordinates of the observed object, except by describing its location relative to the observer itself in natural language. For example, as a result of a crime, terrorist act, natural disaster or natural phenomenon. Observers who find themselves at the scene may transmit a text message that is a vague description of the location of the object or place (for example, the crime scene, the location of dangerous objects, the crash site, etc.). The semantics of the spatial location of the object is further extracted from the text message. Traditional methods of describing topological connections cannot provide a solution to a problem in the case of its cognitive context. Spatial modeling tools integrated into modern GIS are usually designed to work with well-defined features. Therefore, it is urgent to develop methods of spatial modeling for processing fuzzy information, which is a subjective and vague description of spatial relationships in natural language. As well as the development of algorithms for cognitive spatial modeling, which will allow the creation of appropriate software tools for the GIS environment.

2. Literature review and problem statement

The cognitive aspects of human-computer interaction have been actively studied over the past decade, with the aim of creating an effective natural language interface for GIS. In [14], a neural dynamic model is proposed that uses visual input of a real word associated with relational spatial descriptions through a neural mechanism to transform keyframes. In [15], a computational model is proposed that allows mapping natural language expressions into spatial queries, based on a context-enriched semiotic triangle that allows differentiating multiple interpretations. In [10], cognitive spatial reference systems in GIS are considered and fuzzy vector spaces are proposed for approximating the behavior of a neural field using affine transformations.

These studies are aimed at creating new complex computational models for the next generation of GIS. Similar "neural GIS" will appear in the future. However, a large research experience has already been accumulated, which makes it possible to carry out effective spatial modeling using a well-developed mathematical apparatus and spatial libraries of modern GIS. Taking this into account, it is expedient to develop such an approach to identifying a cognitive region, which would be based on the capabilities of existing spatial modeling libraries. In this case, the cognitive aspect of the problem being solved can be provided by the mathematical apparatus of the theory of fuzzy sets and fuzzy logic.

The theory of fuzzy sets is successfully used to describe the geographic location and spatial relationships of undefined objects in GIS. So, in [16], the concepts of fuzzy topology and definitions of fuzzy points, lines and areas for GIS objects are introduced. Based on the concept of computational fuzzy topological space in [17], topological relations between simple fuzzy spatial objects are modeled. In [18], a fuzzy quality assurance system for voluntary geographic information was developed. In [19], a fuzzy 9-intersection model based on the mathematical apparatus of the theory of fuzzy sets is presented. However, these studies do not directly address the issues of visualizing the regions of the spatial location of the object as described by the observer in natural language. Research has focused more on fuzzy representations of spatial objects and formalized topological relationships, rather than on the interpretation of natural language terms into geometric representations.

In [20], an integrated approach to modeling and querying spatio-temporal data related to fuzzy spatial objects and spatial relationships is presented. In [21], basic and complex operators for the SQL language are developed, which can provide fuzzy space-time queries. In [22], a model is presented that provides a complete description in natural language of the inner and outer parts of clear or fuzzy lines and corresponds to the cognitive habits of a person. In [23], an approach to the interpretation of fuzzy semantics of terms of spatial relations in a natural language using a fuzzy random forest algorithm is proposed. These models can handle fuzzy spatial queries. However, the problem of interpreting the fuzzy semantics of cognitive descriptions of spatial relationships in natural language, especially in terms of their display and visualization in GIS, remains poorly understood. Particularly important in this regard are studies that focus on the applied aspects of this problem, allowing the development of software tools for cognitive spatial modeling.

3. The aim and objectives of research

The aim of research is to develop a fuzzy model for identifying cognitive regions in a GIS based on the formalization of observers' phrases in natural language. This will make it possible to develop algorithms for spatial cognitive modeling and, based on them, software tools (scripts) that can be integrated into modern general-purpose GIS.

To achieve this aim, it is necessary to solve the following objectives:

– to propose a way to formalize the phrases of the observer, with which it describes the spatial location of the object, using linguistic variables, and to set the types of the membership function for their terms;

– to develop algorithms for determining and visualizing cognitive regions in GIS taking into account one or more observers, as well as corresponding software tools (scripts) for GIS ESRI ArcGIS 10.5.

4. Materials and methods of research

It is assumed that in most cases, to describe the location of an object relative to its own position, it is enough for an observer to subjectively evaluate and indicate the direction and distance to the object.

Let's introduce the following descriptions of linguistic variables according to [24]:

$$D^{X_{dj}} = \left\{ x / \mu_A^{X_{dj}}(x) \right\}, \quad \mu_A^{X_{dj}}(x) \to [0,1], \quad x \in [0,360], \tag{1}$$

$$R^{X_{rj}} = \left\{ x / \mu_A^{X_{rj}}(x) \right\}, \quad \mu_A^{X_{rj}}(x) \to [0,1], \quad x \in [0,N], \tag{2}$$

where D, R – the linguistic variables "Direction" and "Distance", respectively; X_j – the values of linguistic variables (terms); expression $A=\{x/\mu_A(x)\}$ – a set of ordered pairs of a fuzzy subset A, where $\mu(x)$ – the membership function of the value of the base variable x to subset A.

The direction is a clockwise angle assuming the observer is facing north (0° angle). There are 8 main directions that can be easily identified by a person: in front, behind, left, right, left behind, left in front, right in back, right in front, as shown in Fig. 1.

Fig. 2 shows examples of membership functions for terms X_j of linguistic variable D.

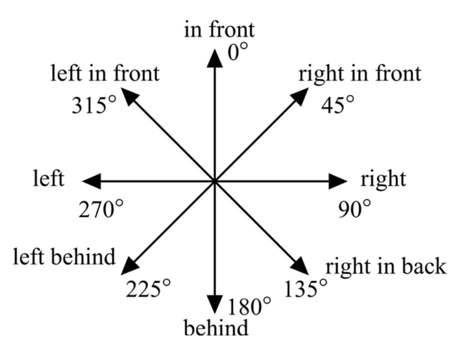

Fig. 1. Values of linguistic variables for determining direction

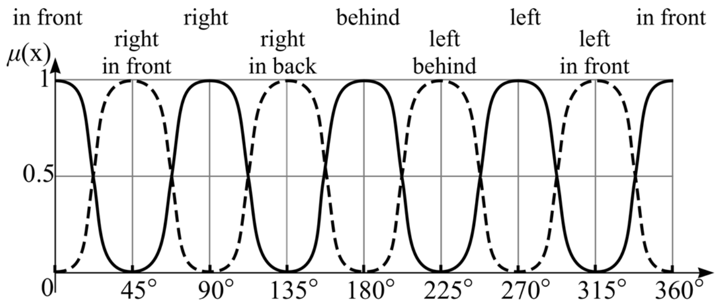

Fig. 2. Membership functions for terms of the "Direction" linguistic variable

The values of the linguistic variable R can be specified in more varied ways. The observer often defines the distance as "near", "close", "not far", "far", etc. In addition, it can be guided by the time it takes to reach the object of observation, and express the distance in the form of terms "within walking distance", "in several steps", etc. In this case, it is necessary to take into account the physical characteristics of the observer, namely the speed of its walking.

Fig. 3 shows an example when the values of the linguistic variable R are given using the trapezoidal membership function.

For the linguistic meaning "in k minutes of walking" in [25] it is suggested to use the membership function shown in Fig. 4. Here ν – the average walking speed, δ – the standard deviation of the walking speed.

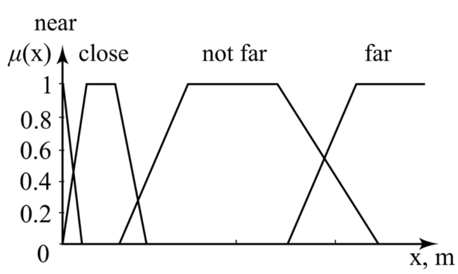

Fig. 3. Membership functions for terms of the linguistic variable "Distance"

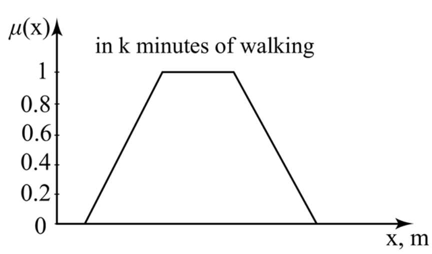

Fig. 4. Membership function for the term "in *k* minutes of walking"

The proposed approach is based on mapping the observer's phrase P={D, R} into a fuzzy spatial area C. Initially, let's define this area as a polygon C^P (Fig. 5).

For polygon C^P [$d1$, $d2$] – the carrier of a fuzzy set for the value of the linguistic variable D given by the observer (in Fig. 5, *a* is an example of a polygon for the term "right"); [$r1$, $r2$] – the carrier of the fuzzy set for the fuzzy value of the linguistic variable R given by the observer.

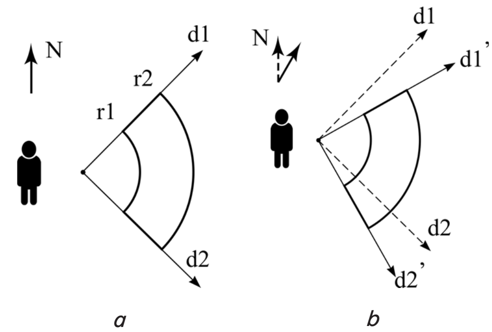

Fig. 5. Representation of the location of the object in the form of a polygon in the GIS: *a* — the observer is oriented to the north; *b* — transformation of coordinates, if the observer is oriented not to the north

If the observer is not oriented to the north, then the transformation of the coordinates of the $C^P \rightarrow C^{P\prime}$ polygon should be performed, as shown in Fig. 5, *b*.

For the further fuzzification procedure, it is advisable to represent the P polygon in the form of a C^R raster, which has the form of a two-dimensional discrete rectangular grid of nxm cells, where $\Delta x=\Delta y=\Delta r$ – the cell size:

$$C^R = \{c_i \mid c_i = n\Delta r, m\Delta r\}. \qquad (3)$$

To shorten (4) can be written in the form:

$$C^R = \{c_i \mid i = \overline{1, n\cdot m}\}. \qquad (4)$$

Let's suggest performing the sampling procedure for the C^P polygon separately to obtain a raster of C^{Rd} directions and a raster of C^{Rr} distances.

To construct a raster of C^{Rr} distances in GIS, the Euclidean distance tool can be used, according to which the value between two point objects $O_1(x_1, y_1)$ and $O_2(x_2, y_2)$ is equal to:

$$ED(O_1, O_2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}. \qquad (5)$$

In the case of a raster data model, the distance from any cell in the raster to the object O_j will be equal to the minimum distance from this cell to each cell that covers the object of interest.

$$ED(O_j, c) = \min_i \{(d(O_j, c))_i\}, \quad i = \overline{1, k}. \qquad (6)$$

Thus, it is possible to construct a raster of distances C^{Rr}, each cell of which contains a value equal to the value of the Euclidean distance ED from it to the point of location of the observer (Fig. 6):

$$C^{Rr} = \{((x, y), ED)_i\}, \quad i = \overline{1, n\cdot m}. \qquad (7)$$

To construct a raster of C^{Rd} directions in GIS, a method can be used that calculates the directional angle of the line for each point of the raster relative to the point of location of the observer.

In a particular case, finding the directional angle between two points A and B is performed in accordance with the following algorithm (Fig. 7):

– calculate the increments of coordinates:

$$\Delta X = X_B - X_A,$$

$$\Delta Y = Y_B - Y_A;$$

from the solution of the right-angled triangle $AB'B$ determine the bearing of the line r_{AB}:

$$r = \operatorname{arctg}\left|\frac{\Delta Y}{\Delta X}\right|;$$

– according to the signs of the increments of coordinates (ΔX, ΔY), it is determined in which quarter of the Cartesian coordinates the given direction is located, and the directional angle of the line α_{AB} is calculated from the known bearing of the line r_{AB} (Table 1).

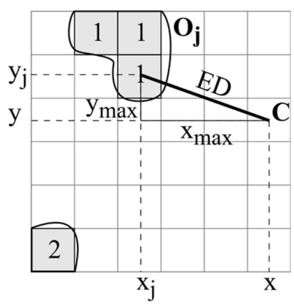

Fig. 6. Scheme for constructing a raster of Euclidean distances

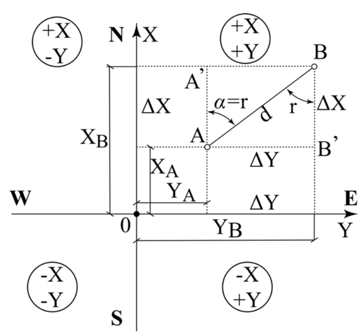

Fig. 7. Graphical representation of the direction angle calculation algorithm

Table 1

Relationship between bearings and directional angles

Quarter	Directional angle value	Bearing name	The relationship between the bearing and the directional angle	Coordinate increment signs	
				ΔX	ΔY
1	0–90°	NE	r=α	+	+
2	90–180°	SE	r=180°–α	–	+
3	180–270°	SW	r=α–180°	–	–
4	270–360°	NW	r=360°–α	+	–

Modern GIS has a large set of library functions that allow converting vector objects to raster and vice versa. For example, the ArcPy library contains functions to convert a raster dataset to point features. Add POINT_X and POINT_Y fields to input point features (Create Fishnet) and calculate their coordinates (Add XY Coordinates) [26]. Thus, the coordinates of all raster points can be retrieved and presented in an attribute table. Further, the calculation of the directional angle for each point of the raster can be performed. When calculating, take into account the type of geometry (in some cases, it is necessary to change the X and Y coordinates in places).

The C^{Rd} directions raster can be obtained by interpolation over a set of points containing the directional angle $p_i.ALF$, for example, using the inverse distance weighted (IDW) method.

The next step is to reclassify the values of the cells p_i.of the rasters of the distance C^{Rr} and the direction C^{Rd} into the values of the degree of membership in a fuzzy set:

$$p_i = \left\{x, \mu_A^{X_j}(x) \mid x \in X_j\right\}, \quad \mu_A^{X_j}(x): x \to [0,1]. \tag{8}$$

Reclassification can be performed on the basis of the membership functions specified for the terms of the linguistic variable D (Fig. 2) and the linguistic variable R (Fig. 3, 4) using the sigmoidal and trapezoidal functions, respectively. As a result, two fuzzy rasters $\tilde{C}^{Rd}$ and $\tilde{C}^{Rr}$ will be constructed (Fig. 8).

In order to obtain a fuzzy region of the object itself, it is proposed to combine the rasters $\tilde{C}^{Rd}$ and $\tilde{C}^{Rr}$ into one using the fuzzy arithmetic operation of intersection (or AND):

$$\bigcap_{j=1}^{n} \mu_A(c_i) = \min\left[\mu_A{}^D(c_i), \mu_A{}^R(c_i)\right]. \tag{9}$$

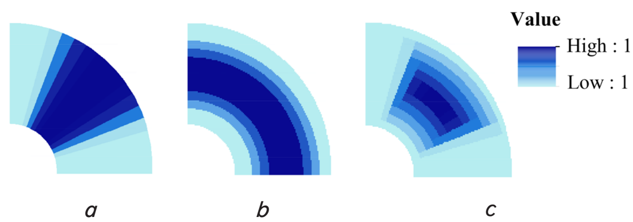

Fig. 8. Result of fuzzy intersection of rasters: *a* — fuzzy raster of distance $\tilde{C}^{Rr}$; *b* — fuzzy raster of the direction $\tilde{C}^{Rd}$; *c* — cognitive region of location of the spatial object $\tilde{C}$

Thus, the proposed approach makes it possible to form a spatial knowledge base, where each phrase of the observer corresponds to a certain fuzzy region of the location of the spatial object.

Let's consider the case when there are more than one observer. Then a fuzzy region is assigned to the phrase of each observer O_i: $P_{Oi} \to \tilde{C}_{Oi}$ The solution can be obtained after combining all regions $\tilde{C}_{Oi}$ into one. For this, raster algebra and various overlay methods can be used, for example, the fuzzy intersection operation:

$$\bigcap_{j=1}^{n} \mu_A^{O_j}(c_i) = \min\left[\mu_A^{O_1}(c_i), \mu_A^{O_2}(c_i) ... \mu_A^{O_n}(c_i)\right], \tag{10}$$

or fuzzy joint operation:

$$\bigcup_{j=1}^{n} \mu_A^{O_j}(c_i) = \max\left[\mu_A^{O_1}(c_i), \mu_A^{O_2}(c_i) ... \mu_A^{O_n}(c_i)\right]. \tag{11}$$

When using (10), the minimum value is selected as the resultant. This ensures that the raster cells with high totals are listed as the potential location of the feature by all observers.

Observers can be assigned importance factors (weights), defined as:

$$W = \left\{ w_i \mid \sum w = 1, i = \overline{1,n} \right\}. \quad (12)$$

Weight indicates the degree of confidence in the observer. The higher the weight of the observer, the more reliable its description of the object's location can be considered. In this case, the imposition of fuzzy regions can be performed using the weighted sum method [27]:

$$c_i = \sum_{j=1}^{n} c_{ij} w_j, \quad (13)$$

where c_i – the final value for the i-th point of the fuzzy region; c_{ij} – the value of the i-th point of the region, built according to the description of the j-th observer; w_j – the weight of the j-th observer; n – the number of observers.

5. Results of the study of the model for determining the cognitive spatial location of an object in a geographic information system

5. 1. Formalization of observers phrases using linguistic variables

Consider an example of the implementation of a fuzzy model for determining the cognitive location of an object based on vague descriptions of observers, made in ESRI ArcGIS 10.5 GIS.

The points of location of three observers and the object of observation (red circle in Fig. 9) were taken as the initial data. The phrases with which observers describe the location of the object, as well as the corresponding reliability weights are given in Table 2.

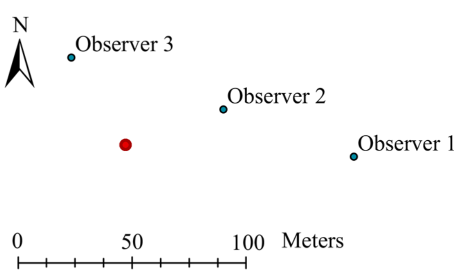

Fig. 9. Location on the map of the observers and the object of observation

Table 2

Initial modeling data

Observer O_i	The value of the linguistic variable R_i "Distance"	The value of the linguistic variable D_i "Direction"	Weight W_i
1	not far	left	0.7
2	close	left behind	0.2
3	close	right in back	0.1

For each i-th observer it is necessary to build a polygon C_i^P. In this case, take into account the coordinates of the location of the observer x_{ob}^i, y_{ob}^i and the linguistic variables $\{R_i, D_i\}$, which determine the direction and distance to the object of observation (Table 2).The quantitative characteristics that define the shape of the polygon: the radius of the circle, the angles of rotation, the lengths of the sides can be determined in accordance with the membership functions shown in Fig. 2, 3. The values of the parameters defining the shape of the polygons C_i^P (Fig. 5, *a*) are presented in Table 3.

Table 3

The values of the parameters defining the shape of the polygon C_i^P corresponding to the fuzzy description of the i-th observer

Observer O_i	Parameter value			
	r1	r2	d1	d2
1	40 m	170 m	225°	315°
2	0	50 m	180°	270°
3	0	50 m	90°	180°

For the membership functions of the linguistic variable *R* (Fig. 3), the following parameters are set: a=10 m, b=50 m, c=100 m, d=150 m.

The membership functions for the values of the linguistic variable *D* are specified as the usual arithmetic product of the values of the S-shaped and Z-shaped membership functions. General view of the sigmoidal function:

$$\mu(x) = \frac{1}{1 + e^{-b(x-c)}}, \quad (14)$$

where c – the coordinate of the transition point ($\mu(c)$=0.5; the same point is the inflection point), b characterizes the slope of the graph. Moreover, b>0 for the S-shaped function and b<0 for the Z-shaped membership function. For the example under consideration, the parameter $|b|$=0.3.

5. 2. Development of algorithms for determining and visualizing cognitive regions

According to the Table 3, a polygon was constructed for each observer. Algorithm 1 describes the procedure for constructing a polygon using the phrase of the i-th observer $P_i=\{D_i, R_i\}$ taking into account its current location (x_{ob}, y_{ob}). The geoprocessing tools of the ArcMap 10.5 package were used: Clip () – clips a part of one polygon, using another polygon as a clip shape; Erase () – creates an output polygon by overlaying the input polygon with an erase polygon.

Algorithm 1: *The construction of the polygon* C^p
Input: *phrase* $P_i=\{D_i, R_i\}$, *observer location* (x_{ob}, y_{ob})
Output: *polygon* C^p
Begin
(r1,r2)← *supp* $\tilde{A}_R$
(d1,d2))← *supp* $\tilde{A}_D$
if r1!=0
C_{r1}^p = *create polygon (type: circle; center:* x_{ob}, y_{ob}; *radius: r1)*
C_{r2}^p = *create polygon (type: circle; center:* x_{ob}, y_{ob}; *radius: r2)*
C_d^p = *create polygon (type: rectangle; top: xob, yob; direction: d1, d2; width: r2)*
if r1==0
C^p = *Clip* (C_{2r}^p, C_d^p)
else
C^p = *Erase* (*Clip* (C_{r2}^p, C_d^p), C_{r1}^p)
End

Next, the polygon C_i^P was discretized in accordance with (7) and Table 1. As a result, rasters of distance C_i^{Rr} and direction C_i^{Rd} are obtained.

The procedure for converting a polygon C^P into rasters of distance C^{Rr} and directions C^{Rd} is described by Algorithm 2.

Algorithm 2: *The convertion of the polygon C^p to distance raster C^{Rr} and direction raster C^{Rd}*
Input: *polygon C^p, observer location (x_{ob},y_{ob})*
Output: *distance raster C^{Rr}, direction raster C^{Rd}*
Begin
raster=Euclidean Distance (point:x_{ob},y_{ob}, cellsize:h, extent: as layer C^p)
C^{Rr}=Extract by Mask (raster, C^p)
point_fs=Add XY Coordinates (Raster to Point (Polygon to Raster(C^p, cellsize:h)))
foreach p_i in point_fs
p_i.DX=p_i.Point_X−x_{ob}
p_i.DY=p_i.Point_Y−y_{ob}
*p_i.R=arctan(abs(p_i.DY/p_i.DX))*180/PI*
if p_i.DX>0 and p_i.DY>0
p_i.ALF=p_i.R
else if p_i.DX<0 and p_i.DY>0
p_i.ALF=180−p_i.R
else if p_i.DX<0 and p_i.DY<0
p_i.ALF=180+p_i.R
else
p_i.ALF=360−p_i.R
C^{Rd}=IDW(point_fs, value: ALF, cellsize:h)
End

According to Algorithm 3, which provides for the procedure for reclassifying raster cells C_i^{Rr} and C_i^{Rd} in accordance with their belonging to a fuzzy set, fuzzy rasters $\tilde{C}_i^{Rd}$ and $\tilde{C}_i^{R}$. were built. Cognitive region of the object location for each observer was selected by combining rasters $\tilde{C}_i^{Rd}$ and $\tilde{C}_i^{R}$ using a fuzzy intersection operation (9). The results of modeling cognitive regions are shown in Fig. 10.

Algorithm 3: *The construction of the cognitive spatial location $\tilde{C}$*
Input: *distance raster C^{Rr}, direction raster C^{Rd}*
Output: *cognitive spatial location $\tilde{C}$*
Begin
$\tilde{C}^{Rd}$=Reclassify (C^{Rd}, value: $\mu_A^D(x)$)
$\tilde{C}^{Rr}$=Reclassify (C^{Rr}, value: $\mu_A^R(x)$)
$\tilde{C}$=Fuzzy Overlay ($\tilde{C}^{Rd}$, $\tilde{C}^{Rr}$, overlay type: AND)
End

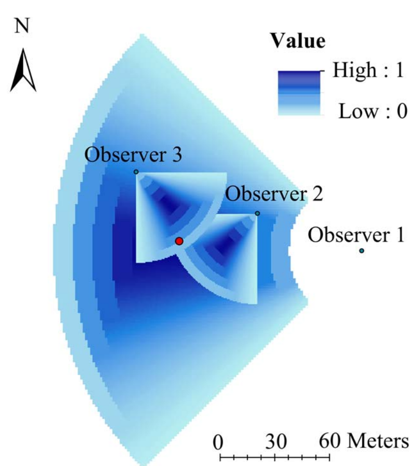

Fig. 10. Results of modeling cognitive regions according to vague descriptions of the observer

To find the final cognitive region, the overlay operations AND (10), OR (11) and the weighted sum (12) were used. The simulation results are shown in Fig. 11. The black circle marks the location of the observation object (the radius of the site is 2 m).

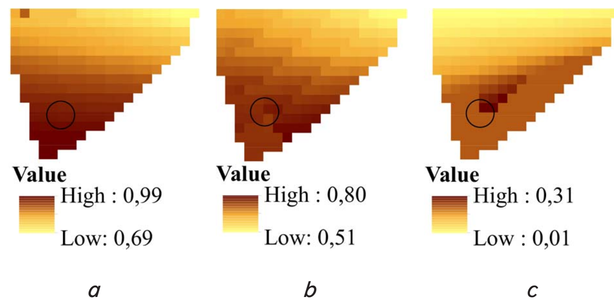

Fig. 11. Results of modeling the final cognitive region: *a* — AND overlay operation; *b* — OR superposition operation; *c* — overlay operation weighted sum

Let's note that the use of the fuzzy intersection operation (10) results in an estimate based on only the lowest value, while the fuzzy join operation (11) takes into account only the highest values of the raster cells of all observers. In both the first and second cases, there may be errors associated with underestimation or overestimation, respectively. The trade-off between the two extremes is to use a weighted overlay technique to compensate for the low values of one observer with the high values of the other. That is, the weighted sum in this case can be regarded as an operation of fuzzy averaging. However, for its application, it is necessary to calculate the weight coefficients, which is not always possible.

6. Discussion of the results of modeling the cognitive spatial location of an object in a geographic information system

Fuzzy regions obtained using the OR superposition operation (Fig. 11, *b*) and a weighted sum (Fig. 11, *c*) correctly identify the location of the object. Their areas with the highest values (more than 0.7) have blurred boundaries and an area exceeding the area of the object, since they take into account the maximum values of the rasters belonging to all observers. When using the AND superposition operation (Fig. 11, *a*), the area with the highest membership values (more than 0.3) is clearly expressed and displaced by less than 2 m to the northeast from the real location of the object.

An important parameter for modeling is the raster cell size. It is assumed that it must be the same for all simulated regions for the correct blending operation to be performed. It should be selected taking into account the distances analyzed and the required simulation accuracy. In the example, the cell size of the raster is 1.56 m.

Of course, the obtained simulation results are influenced by how reliably the observers themselves determine the location of the object. Therefore, it would be incorrect to evaluate the modeling accuracy for a model that initially relies on subjective input data. So the object of observation was on the border of directions ("left" and "left behind" for observer 2 and "right behind" and "behind" for observer 3), as well as on the border of distances expressed by the terms "close" and "not far". This skewed the bottom line. More direction vectors and distance terms could be specified. However, the use of more than 8 directions will complicate the task of the observer in determining and describing the location of the object in natural language.

Thus, an important feature of the presented model is its orientation towards human cognitive habits. This aspect was not directly taken into account in the previously developed fuzzy approaches to describing the uncertainty of topological relations [17, 19] and fuzzy space-time queries [20, 21]. In addition, the developed algorithms for determining cognitive regions in GIS are based on the functionality of modern spatial modeling libraries and therefore can be integrated into all popular GIS.

The proposed approach to defining cognitive regions in GIS can be used in different subject areas. For example, when conducting historical research to determine the location of historical objects that have not survived to this day. Spatial location can be obtained from historical documents and records of contemporaries. In addition, the approach can be applied in forensic science when reconstructing the picture of a crime. It allows to determine the authenticity of the descriptions of witnesses, to identify contradictory and false testimony of eyewitnesses.

Let's note that when using the model, restrictions on the input data must be taken into account. A prerequisite is the availability of accurate information about the geolocation of the observer. All graphic constructions of vector objects in GIS are tied to the coordinates of the observer. The observer should be oriented to the north. It is possible to transform coordinates, but this requires accurate information about the current orientation of the observer in space. In addition, the approach of binding to the coordinates of the terrain by the position of the observer to objects clearly defined in space ("reference points") deserves consideration. For example, an observer can define the location of an object as "next to a church", "two meters to the left of a monument", "to the right of a university," and the like.

The model assumes the presence of a spatial knowledge base containing linguistic variables and the corresponding cognitive regions. The study does not consider the organization of such a knowledge base and spatial queries to it. The main focus is on formalizing observer phrases and the process of defining cognitive regions in GIS. In addition, issues related to the linguistic and cultural characteristics of the definition of "place" are not considered. The set of linguistic variables may differ for different languages and should be adapted to suit national circumstances. These aspects, as well as the problems associated with extracting the semantics of spatial location directly from the observer's text message, can be a further vector for the development of this research.

7. Conclusions

1. An approach to solving the problem of fuzzy determination of the spatial position of an object in GIS based on a vague description of observers in natural language is proposed. The model is based on the formalization of the observer's phrases, with which it can describe spatial relations, in the form of a set of linguistic variables that determine the direction and distance to the object of observation. Membership functions are given for the values of linguistic variables, which take into account the cognitive habits of users. The direction is defined as the angle clockwise from the observer's position point to the north (0° angle). The linguistic variable «Direction» has eight terms that can be easily identified by a human.

2. Algorithms for constructing fuzzy regions in GIS and methods are developed, with the help of which they can be superimposed to obtain a fuzzy location of an object. A spatial knowledge base can be built from a set of phrases in natural language and corresponding fuzzy regions. An example of the implementation of a fuzzy model for identifying cognitive regions based on vague descriptions of observers in the ESRI ArcGIS 10.5 GIS environment using specially developed scripts is considered. The modeling results show that the proposed approach allows transforming cognitive descriptions of the location of an object into quantitative and qualitative geographic information and presenting it in a raster data model in a GIS. The proposed solution can be used in applications which work is based on the interpretation of fuzzy semantics of cognitive descriptions of spatial relationships in natural language.

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