

Measuring Spatial Dependencies of Various Spatial Objects Related To the Road Safety Discrepancies



Charankumar Ganteda, Shobhalatha G, Rajyalakshmi K

Abstract: Spatial analysis is very much useful and gives better results in analyzing the data related to graph theory in various fields with spatial contexts. Defining the spatial location of the entities being studied are the fundamental problem in the spatial analysis. Spatial graphs and mathematical tools plays a vital role in the analysis of spatial data. In this paper, we made an attempt to understand the spatial graph properties and it can be used to describe, compare as well as to test specific hypothesis of road safety measures with respect to specific locations. The integration of Graph theory, statistical measure such as spatial autocorrelation and Geographical information system (GIS) provides a scientific platform for measuring the entities involved in road safety. In this connection, we collect the information in different specific locations related to several discrepancies which affect the road safety. Identify the locations with low safety in our study region and measured the similar objects which are close to other close objects by using Moran's I index. Our main objective is to determine the observed spatial pattern of low safety values is equal to any other spatial pattern. Spatial dependencies with respect to the various discrepancies cause to the low safety and suggest measures to take the precautionary steps when moving from one location to another. From the examined results, we conclude that the similar values grouped together in a map and also observed that the spatial auto correlation, the qualities at one area do not rely upon qualities at other neighboring areas.

Keywords: Dijkstra's algorithm, Moran's I index, Road discrepancies, spatial auto correlation, Spatial structure.

I. INTRODUCTION

Spatial analysis or spatial statistics incorporates numerous systems and concentrate the substances like geological properties. Spatial analysis has assortment of strategies utilizing various methodologies connected different fields most prominently in the investigation of geographic information. The basic issue in the spatial investigation is characterizing the spatial area of the elements being considered. Epidemiology contributed with early work mapping on outbreak cholera. The spread of disease and with location studies for health care delivery. John snow (1854) first uses of map based spatial analysis. Birch (1997) introduced Clustering Algorithms and its Applications for

new data. Kobayashi (1997) provides generalization on a spatial graph theory. Gyananath et al. (2001) assessed environmental parameter on ground water quality. Structural landscape connectivity developed by using algorithms of spatial graph (Fall et al 2007 and Dale and Fortin, 2010). Spatial regression should consists of three main categories depending on how spatial influences modelled (Dormann et al., 2007 and Beale et al 2010): i) space incorporated in covariate predictors ii) space involved in error term iii) spatial impacts in the response or explanatory variables are replaced by changing the original data. Moran (1950) tested spatial dependency based on the spatial autoregressive model. Dale and Fortin (2010) described the transition from graphs to spatial graphs. Griffith (2011) studied spatial autocorrelation and filtering through scientific visualization. Prudhomme et al (2013) identified spatial autocorrelation in take-up of antenatal thought and relationship to nuclear family unit and town level elements: results from a community based survey of pregnant women in six districts of western Kenya. Fanc and Myint (2014) compared spatial autocorrelation and landscape metrics are helpful to measure urban landscape fragmentation land scape and urban planning. Russell R. Barton (2015) developed simulation Metamodelling. Ali Moradi et al (2016) did spatial examination to recognize high hazard zones for traffic crashes. Erica Flapan et al (2016) developed spatial graphs to intrinsic knotting and linking results. Kamaldeep singh et al (2017) studied modeling of urban road traffic using spatial graph theory. Mark altaweel (2017) provided GIS and spatial autocorrelation, analysis.

Spatial dependency or autocorrelation in Geographical Information system (GIS) helps to understand degree to which one object is similar to other many objects. Several authors suggested different approaches to measure the spatial autocorrelation. It measures how much close objects are in comparison with other close objects. The entire statistics depends on the observations which are being independent from one another. The existence of the map, violates the fact that the observations are independent from one another. Hence, spatial correlation is used to identify the observations are independent from one another. Moran's I is a measure to find the spatial relation between the entities developed by Patrick Alfred Pierce Moran. It will be characterized by a correlation that occurs among sample that are geographically close. By measuring spatial autocorrelation we can determine how spatial patterns occur in our study area. Moran's I treat as a global measure to which takes the entire data set and produces a single output value.

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*Correspondence Author(s)

Charankumar Ganteda*, Research scholar, Department of Mathematics, Srikrishna Devaraya University, Anantapuramu, India.

Shobhalatha G, Department of Mathematics, Srikrishna Devaraya University, Anantapuramu, India*,

Rajyalakshmi K, Department of Mathematics, Koneru Lakshmaiah Education Foundation, Guntur, India

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A matrix form is useful and conventional approach to represent a graph. Graph theory widely used in the many applications such as in electrical network analysis and operations research, matrices representation also turn out to be the natural way of expressing the problem. Praveen and Rama (2017) studied A K- Means Clustering algorithm on Numeric data. Graph theory provides mathematical knowledge, based on simple concepts, in which structural units are represented as nodes with relationships between them depicted as lines. The nodes may have quantitative and qualitative characteristics, and the edges have the properties such as directions and weights. In this regard, we identified the applications of graph theory in measuring the road safety discrepancies with the properties of spatial contexts. Here we made an attempt to show how the spatial graph properties can be used for describing and comparison as well as to test specific hypotheses. Road safety measures will prevent the road users from being killed or seriously injured. In this context, we use graph theoretic techniques such as Dijkstra's algorithm to find the shortest route between the locations and identified the spatial autocorrelation between the locations by using Moran's I index and observed the similarities between the objects.

II. METHODOLOGY

First we will review the existing literature concerned with spatial graphs and how it exhibits the similarities with respect to the specific locations can be studied.

A. Data used

To carry out this research work the researcher has taken data from the 340 samples from different specified locations from Hanuman junction to Vijayawada through primary and secondary sources. Here we integrate the spatial graph theory and the mathematical approaches to identify the discrepancies of road safety.

B. Spatial Graph theory

Spatial graph provides a graph in the 3-dimensional Euclidean space R^3 or the 3-sphere. For a graph G we take an embedding $f: G \rightarrow R^3$ then the image of spatial graph of G can be represented by $\bar{G}=f(G)$. It is a generalization of Knot and link. Dale and Fortin (2010) described the transition from graphs to spatial graphs.

A distance between two vertices U and V of a associated or connected graph is the length of the shortest path connecting them. For an associated graph G ,

$$E(V)=\text{Maximum dist}(V,x) \text{ the eccentricity of } V \text{ in } G.$$

$$D(G)=\text{Maximum } E(V) \text{ is the diameter of a } G$$

$$R(G)=\text{Minimum } E(V) \text{ the radius of } G.$$

Definition of Network: A Network consists of a set of nodes connected by circular segments. The documentation for depicting a system is (N, A) , Where N is the arrangement of nodes, and A is the arrangement of curves. A network system is said to be associated if every two distinct nodes are connected by at least one path. A tree is a cycle free connected network involved a subset of the considerable number of nodes, and a spanning tree is a tree that connections every one of the nodes of the network. The minimal spanning tree joins the nodes of a network utilizing smallest total length of interfacing

branches.. The minimal spanning tree helps to provide the most economical and reduce the cost of the design of the road system. The shortest-route problem decides the shortest route between a source and destination in a transportation network. Dijkstra's algorithm provides the shortest routes between the source node and each other node in the system.

C. Dijkstra's algorithm: (Ref. 6, Page No. 247-248):

Let d_i be the shortest distance from source node 1 to node i , and define $\phi_{ij}(\geq 0)$ as the length of the circular segment (i, j) . The algorithm characterizes the label for an immediately succeeding node j as

$$[d_j, i]=[d_i+\phi_{ij}, i], \phi_{ij} \geq 0 \quad (1)$$

The name for the starting node is $[0,-]$, showing that the node has no antecedent. There are two types of node labels in Dijkstra's algorithm are temporary and permanent. A temporary mark at a node is altered if a shorter route to the node can be found. Otherwise, the transitory status is changed to permanent.

1. Mark the source node (node1) with the permanent label $[0,-]$. Set $i=1$.

2. General step i

i) Compute temporary marks $[d_j, \phi_{ij}, i]$ for each node j with $\phi_{ij}>0$, provided is not permanently named. If node j already has an existing temporary label $[d_j, K]$ through another node K and if $d_i+\phi_{ij}<d_j$, replace $[d_j, K]$ with $[d_i+\phi_{ij},i]$.

ii) If all the nodes have permanent marks, stop. Otherwise select the label $[d_r, S]$ having the shortest distance $(=d_r)$ among all temporary labels (break ties arbitrarily). Set $i=r$ and repeat step i .

D. Moran's I index:

Moran's I is a spatial statistic which measure the spatial autocorrelation. It measures how much close objects are in examination with other close objects. It can be referred as positive, negative and no spatial relation between the entities. Positive correlation indicates that the similar values group together in a map. Negative spatial correlation represents the dissimilar values group together in a map. In general, we assume important property that the observation being independent. If

Table: 1 Frequency of Discrepancies in different locations in the selected area

S. NO	DISCREPANCIES	NO OF POINTS	Prob ability
1	Bridges	20	0.06
2	Culvert/curve	110	0.32
3	Gap in medians	115	0.34
4	Industry/Instiue/Intersections	67	0.20
5	bus or truck bays	15	0.042
6	Pilgrimages/shandy/Tollplaza	13	0.038

autocorrelation exists in the data, then the property will be violated. Spatial autocorrelation gives us an idea about the clustering or dispersion in a map.

Generally, spatial autocorrelation requires observations and locations.

Patrick Alfred pierce Moran has developed formulae to find the spatial autocorrelation is given by

$$I = \frac{N \sum_i \sum_j w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum \sum w_{ij} \sum (y_i - \bar{y})^2}$$

(2)

Table: 2 Identification of the locations with Low road safety based on the discrepancies -Distance matrix of low safety locations

Where N gives the number of objects or spatial units indexed by i and j

	Spatial autocorrelation				
	Moran's I value	Observed	Expected	SD	p-value
Low safety locations	0.1888	0.1888	-0.2	0.28	0.1701
Out of 300 locations -Location point 23 culvert, Location 97 culvert, location 99 culvert, 162 minor bridge, 286 intersection, 315 service road					

y is the variable of interest, \bar{y} is the mean of y, w_{ij} is a matrix of spatial weights with zero's on the diagonal (ie., $w_{ii}=0$) and w is the sum of all w_{ij} .

Similarity = $(y_i - \bar{y})(y_j - \bar{y})$, similarities between units is calculated as the product of the difference between y_i and y_j with the overall mean.

1. I=-1 represents perfect clustering of dissimilar values or perfect dispersion.
2. I=+1 represents perfect clustering of similar values or perfect precision
3. If I=0 no auto correlation or perfect randomness.

By using spatial autocorrelation, we set null hypothesis that the observed spatial pattern is similarly likely as some other

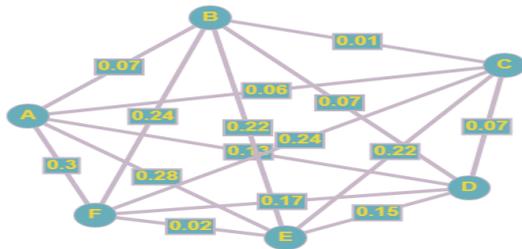


Figure 3: Graph representing the distance from one location to another

spatial pattern or the qualities at one area do not rely upon qualities at other neighboring areas.

III. RESULTS AND DISCUSSION

In the selected area, we identified different locations with low safety based on the discrepancies occurred in that area. In the following table, we present the type of discrepancies with probability and the map of our study area.

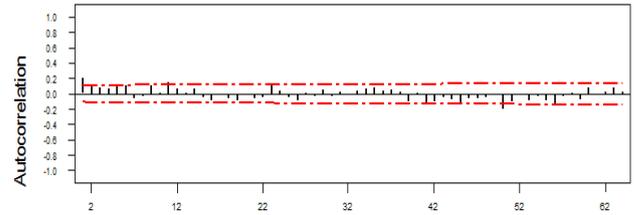


Figure 2: Autocorrelation function for safety points of all Locations.

By measuring spatial autocorrelation we can determine how spatial examples happen in our informational collection or study zone. We can see that the sets of locals show above or beneath average scores will contribute positive terms to the numerator. When the pairs of regions where one region exhibits above average scores and the other below the average will contribute to the negative terms.

Table: 3 Spatial autocorrelation of low safety locations

	1	2	3	4	5	6
1	0.0666	0.0587	0.1329		0.2791	0.2975
2	0.0666	0	0.0135	0.0675	0.2172	0.2354
3	0.0587	0.0135	0	0.0743	0.2213	0.2396
4	0.1329	0.0675	0.0743	0	0.1510	0.1690
5	0.2791	0.2172	0.2213	0.1510	0	0.0185
6	0.2975	0.2354	0.2396	0.1690	0.0185	0

Data related to low safety locations have identified by using Geoda software and observed that A has neighbors B and C; B has neighbors A, C and D; C has neighbors A, B and D; D has neighbors E, B and C; E has F and D; F has its neighbor E. By applying Dijkstra's algorithm to the above data we obtain the following graph with desired route is A→C→B→D→E→F with a total of length of 0.31 miles. We find shortest route between first location and every other location in the network. From equation (2), we calculate spatial autocorrelation for '6' locations that we identified with lowest safety among all other locations. We get the Moran's I observed value is 0.1888 it indicate that there exists a positive spatial autocorrelation between the locations. Hence, we conclude that the similar values grouped together in a map. From the examined results we observed that the spatial auto correlation, the qualities at one area do not rely upon qualities at other neighboring areas.

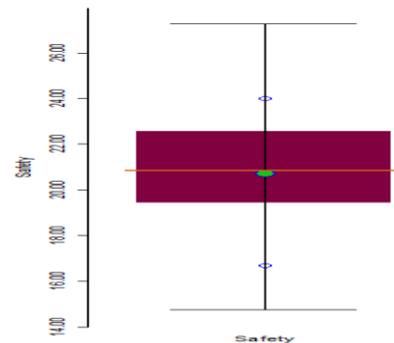


Figure 4: Box plot and Moran's I Map of Low safety locations

In figure 4, Green color circle represent the mean value, Red portion covers 25% - 75% range values, orange line represents median, black lines indicates normal distribution of the data and finally the circle outside the black line are outliers. There is no outlier present in the data.

IV. CONCLUSIONS

In this paper we made an attempt to integrate spatial graph theory, spatial autocorrelation to the specified selected locations. To carry out this, we identified '6' locations with lowest safety among 340 locations. Dijkstra's algorithm and Geoda software are providing the minimum spanning tree and graphical representations along with neighboring locations from one to another. We determine the distance matrix to the identified locations and sketch network diagram from one to another location and studied the spatially related objects by the method of autocorrelation and Moran's I index, it exhibits similar values clustering together in a map. we calculate spatial autocorrelation for '6' locations that we identified with lowest safety among all other locations. We get the Moran's I observed value is 0.1888 it shows that there exists a positive spatial autocorrelation between the locations. Hence, we conclude that the similar values grouped together in a map. From the examined results we conclude that the qualities at one area do not rely upon qualities at other neighboring areas.

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AUTHORS PROFILE



He completed his M.Sc. Mathematics in Andhra University and has published 8 Research papers in various referred journals. He has membership in professional societies like IAENG and APSMS.



She has been working as Professor in the department of Mathematics, Srikrishna Devaraya University and completed her Ph. D from S V University. She Published 70 research papers in various referred national and international journals. She has membership in various professional societies



She got her Ph. D from Acharya Nagarjuna University and Published 25 research papers in various national and international referred journals. She has been working as Assistant Professor, Department of Mathematics, K L University and associated with the professional societies IAENG, ISRD.