ORS: The Optimal Routing Solution for Smart City Users

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Abstract

Road transport-related air pollution is one of the critical issues for most of the developing countries as the emission of air pollution during transportation causes severe physical and psychological health problems. Hence, the identification of pollution-free route is the most critical aspect in the case of air pollution management for smart city users. This research paper proposes an optimal routing solution algorithm (ORS) approach that predicts the pollutant value for the road network and includes a weight assignment function to measure the safety level of each route to build a developed transportation system for smart city users. The proposed method experimented with both geostatistical and non-geostatistical algorithm to predict the SPM pollutant level in each route. Each approach is evaluated to compute the weight function to determine the optimized routing solutions. The streamlined routing solution can be accessible by the developed web applications to access the healthier path, which may not provide the shortest path every time but suggests a more robust route for smart city users.

Keywords: Air Pollution, Spatial Analysis, Geostatistics, Transportation

1.1. Introduction

Road transportation is the oldest means of communication in India. In developing countries like India, it covers all the areas and facilitates to provide door to door services. Due to modernization, several ways have been developed to travel across roads. This modernization phenomenon has also brought several negative impacts on environments like the increasing level of air pollution due to overcrowded routes. These busy streets bring high risk to the general public, like adverse effects on the environment and human life. So, air pollution has become one of the most complicated environmental issues due to its negative impact on human health. The transportation system has become a severe issue in India, more specifically due to road congestion and the increasing level of pollution generated due to traffic congestion. Due to the high air pollution exposure, it is challenging to execute plans to develop a smart transportation system for smart city users as it causes severe health issues at nearby locations of toxic spots [1]. Therefore, there is a need to minimize traffic congestion that increases due to the high level of air pollution at highways. Hence, it is also essential to get notified of the air pollution level in routes, to prevent diseases and plan daily activities accordingly. Thus transportation has become a basic challenging problem in everyday life of citizens in a smart city. This issue can be solved by spatial analysis of pollution levels at each location. As it is complicated to make the construction of roads for smart city users due to the limitation of resources and land use, it is better to enhance transportation quality by minimizing air pollution and its negative impacts.

Following the introduction, the rest is organized as follows. Section 1.2 represented state of the art, Section 1.3 and Section 1.4 includes the proposed system model and results and discussion. Section 1.5 presents the conclusion and future work part of this research paper.

1.2. State of the art for routing solutions

Zahmatkesh et al. [2] used air quality index as a standard to build urban travel route planning. The optimum route-finding based on the Dijkstra shortest path algorithm and AQI value. The author included a combination of both the parameters as a weight function to find the optimum path. Sharker et al. [3] also present a similar type of approach which differentiates the shortest route and the least air pollution exposure route in terms of distance, time, and air quality index. Determine the source of pollution level is also a crucial part of pollution management. Therefore, j.briggs et al. [4] studied the causes of air pollution and proposed a regression-based approach for mapping traffic generated air pollution using spatial analysis techniques. Li et al. [5] also studied the source of increased levels of air pollution and its health impact during the different modes of transportation. The author suggested walking communication instead of motorcycles to minimize the pollution level. Vamshi et al. [6] attempted to reduce the pollution level by reducing its source of origin. He developed a framework based on Internet of things which distributes the traffic uniformly by providing diversion suggestion during peak traffic duration, and therefore it reduces the traffic generated air pollution. Few types of research have been conducted to compute the real-time pollution value on each route. Ramos et al. [7] proposed a senor network to identify the pollution level of each journey and provides all functionality that can give the user all the facilities to trace the least polluted route amongst all possible ways.

Though all the existing work is made to alert citizens and focused on people's security, these applications are not user-friendly to access the analyzed information and also not able to compute global variations of air pollution to predict pollution level accurately. So based on this study, the proposed work proposed a method to predict the pollutant value of each route more appropriately to find an optimal routing solution(ORS) for smart city users. The proposed system model is explained in the next section.

1.3 Proposed System model

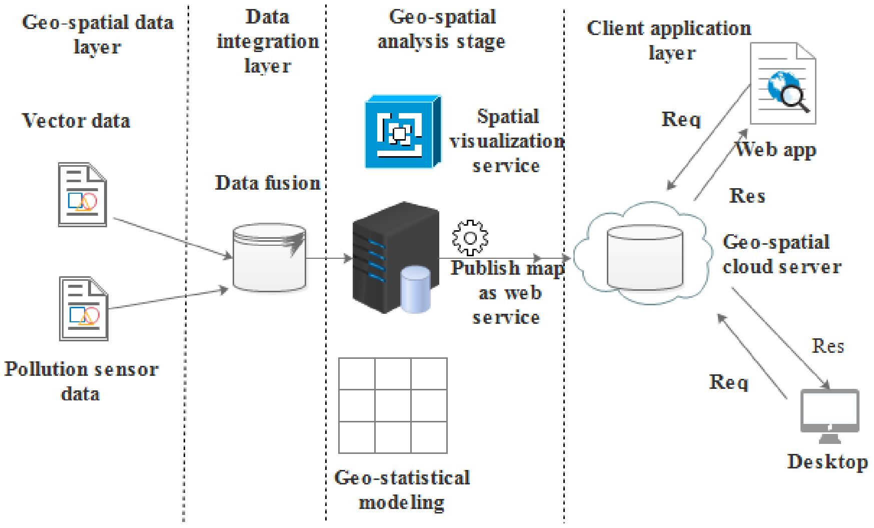

Fig.1.1. Proposed system model

The proposed system model is a technology-based framework that consists of multiple components. **Fig.1.1.** represents the proposed framework consists of the geospatial data layer, data integration layer, geo-spatial analysis stage, client application layer. Geo-spatial data layer includes data of air pollution monitoring stations, IoT based devices. Data integration(DI) layer builds the data fusion model, which integrates study area coastline, natural, highway, administrative vector data, and IoT sensor device data. The geo-spatial analysis stage takes data fusion data as input and implements a geostatistical model to generate spatial interpolation maps. This stage provides map layer services that publish interpolation maps to the cloud server, where the navigation map will create a routing service based on the map service layer after the client application layer HTTP request. The client application layer supports web and desktop as a client to start request(Req)-response(Res) service with a cloud server to visualize the routing solution for a better decision.

Based on the system model, few things have been presented in the following subsection, such as study area, proposed spatial interpolation model, cross-validation, weight assignment, publish the map as a web service.

1.3.1. Study area

This study is carried out at Orissa (India). It extends between the latitudes (17.780N and 22.730N) and between longitudes (81.37E and 87.53E), which covers an area of 155,707 km2. This state is in the northeastern part of India. A historical dataset of several pollution monitoring locations, collected from Odisha central pollution control board [8], is used to identify the spatial distribution of pollution levels across several geolocations of Odisha. Road networks also included in the base map during the spatial analysis of pollution over routes. During the study, it found that the SPM level is very high at Orissa as compared to other pollutants. Hence, SPM considered as a source of interest to identify the safety level at each route.

1.3.2. Spatial interpolation model

The empirical bayesian kriging (EBK) model is used as a spatial interpolation model in the geospatial analysis stage. It is a geostatistical algorithm that automates the process of developing a kriging model. It follows the sub-setting and simulation procedure to adjust the parameter while developing a valid model automatically. It accounts for the error generated by the semivariogram model, which is possible by estimating and implementing many semivariogram models instead of one model. During the first iteration, it predicts a semivariogram model from the existing dataset and simulates a new value at each input location. Those simulated data are used to build a new semivariogram model and uses Bayes' rule to assign a weight to that model. The repetition of this process will compute standard prediction error at each unmeasured locations and generates a semivariogram spectrum. The distribution of such a semivariogram represented in **Fig.1.2.**, where blue crosses signify the empirical semi variances and solid red lines represent the median of the distribution

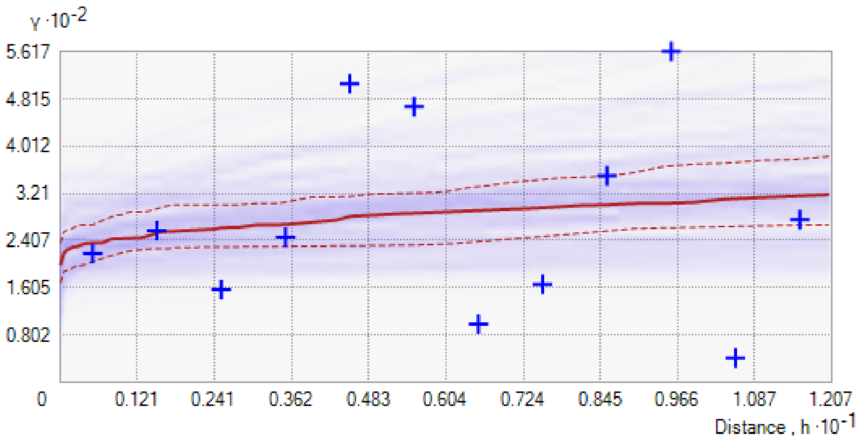

Fig. 1.2. Distribution of the semivariogram model shaded by density.

EBK model utilizes three types of semivariogram model which can are expressed as shown in equation (1)-(3) [9]:

Power $\gamma(h) = \text{Nugget} + b|h|^a$ (1)
Linear $\gamma(h) = \text{Nugget} + b|h|)$ (2)
Thin plate spline $\gamma(h) = \text{Nugget} + b|h|^2 * \ln(|h|)$ (3)

Where h, b represents distance and slope, respectively. After the successful estimation of the semivariogram at each iteration, EBK generated an interpolation map with the help of some semivariogram model, as shown in **Fig. 1.3.**, here color scale indicates the SPM value over the layer.

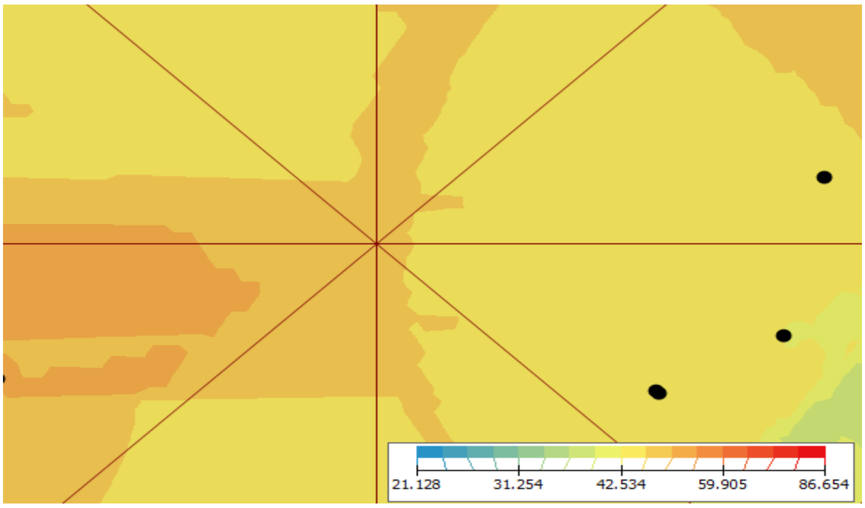

Fig. 1.3. SPM layer generated using EBK.

1.3.3. Cross-Validation

The Leave-One-Out Cross-validation(LOOC) technique is adopted to compare the performance of the proposed model with the inverse distance weighting (IDW) model in ArcGIS[10]. The achievement of those models is estimated based upon their standard prediction error, and therefore, Root Means Square Error(RMSE) and Mean Error(ME) evaluated to measure the performance. **Table 1.1.** shows the RMSE, and MSE value for both the interpolation technique and found that EBK outperforms the IDW method for non-stationary data and provides better performance for generating the continuous surface.

Interpolation/error metrics	Inverse distance weighting	EBK
Root Mean Square Error (RMSE)	19.4994	16.3527
Mean Error(ME)	0.8302	-2.1326

Table 1.1. comparison of error metrics

1.3.4. Weight assignment

Due to the non-uniform structure of air pollution monitoring stations, it is challenging to identify the spatial correlation among them and hence, to determine the pollution level at each road segment for a given source and destination. This work followed the weighting scheme and compared the weight of each route, to estimate the least polluted way among all possible paths. The weight computation method depends upon the interpolation value and travel distance to cover a segment. Therefore, EBK and IDW algorithms can be implemented for experimental purposes. Due to the high performance of EBK, it is considered to get SPM prediction value. During EBK implementations, the k-nearest neighbor technique is adopted to reflect the impact of interpolation points on the interpolated points. Here, 4 number of minimum neighbors and 8 number of maximum neighbors is considered during EBK SPM spatial distribution. Algorithm1 shows the spatial interpolation technique performed during the work. Once we get the continuous level of SPM value, it is possible to assign a weight to each route to quickly identify the optimal solution from source to destination, which is represented in Algorithm 2.

1.3.5. Optimal routing algorithm

Algorithm 1 Spatial-temporal interpolation algorithm

Input: Pollutant value at discrete points
Output: Continuous surface of pollutant
1: Temporal-spatial interpolation:
2: **if** time column values are not continuous **then**
3: **for** each measured point $\{a_1, b_1\},\{a_2, b_2\},\{a_3, b_3\}\ldots\ldots\{a_n, b_n\}$ **do**
4: linear interpolation
5: **end for**
6: **end if**
7: **if** SPM value is sparse **then**
8: **for** each measured point $\{a_1, b_1\},\{a_2, b_2\},\{a_3, b_3\}\ldots\ldots\{a_n, b_n\}$ **do**
9: Compute EBK interpolation
10: **end for**
11: **end if**
12: SPM prediction value $\leftarrow$unmeasured points $\{c_1, d_1\},\{c_2, d_2\},\ldots\ldots\{c_n, d_n\}$
13: **return** SPM polygon prediction map with class level c

Algorithm 2 Computing the least polluted route
Input: Source point, destination point, start time
Output: Optimal route, directions, distance, travel time
1: Perform spatial-temporal interpolation:
2: Continuous surface of SPM $\leftarrow$ Call algorithm 1
3: **if** the user is a driver **then**
4: driving distance(d) $\leftarrow$ transportation mode
9: **end if**
10: Estimate weight(w) of each route(i):
11: $\sum_{i=1}^{n} R_{\omega_i} = c*d$
12: $\sum_{i=1}^{n} R_{\omega_i} \leftarrow$ Route
13: Find the optimal path, having $\min\left(\sum_{i=1}^{n} R_{\omega_i}\right)$
14: **return** The optimized route

1.3.6. Publish the map as a web service

The interpolation output is projected to a WGS84 coordinate system to support the features on the web. After generating the EBK interpolation polygon map, it can be published to ArcGIS Online as a web service to design a web application. The highly polluted area can be treated as barriers to provide the safest routing services to drivers and pedestrians. Here, we have developed a web map application, which computes the polluted area and considers it as barrier points for different transportation modes.

1.4 Results and discussion

The navigation map is selected to find out the area of interest and intended navigation routes within that area. Direction service enables the user to display the direction while traveling towards the destination with an optimized travel time solution. High level interpolated polygon is treated as barriers points during different types of travel modes to obtain an optimal solution. Stops, barriers are the routing parameters that are intended to modify the waypoints for getting an optimized routing solution. Travel time is another most important feature, which is considered to get an optimized solution. The default transportation mode provides optimized travel time for small automobiles such as cars. This streamlined solution for a car driver represented in **Fig. 1.4.**, **Fig. 1.5.**, with and without restrictions points.

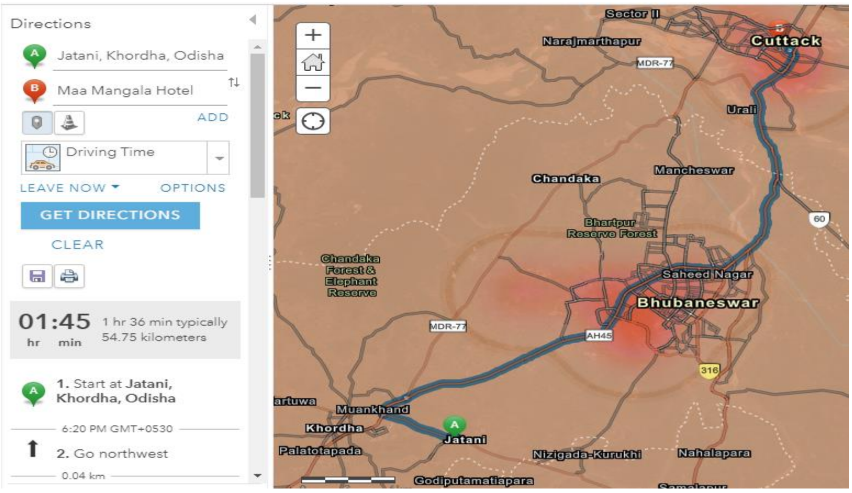

Fig. 1.4. The most SPM polluted route

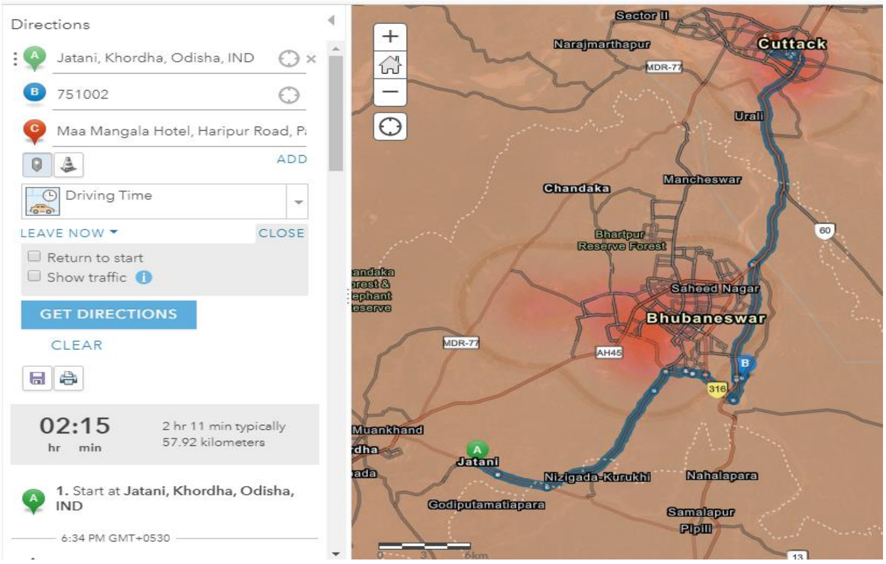

Fig. 1.5. The least SPM polluted route

The driver requires 1 hour 45 minutes to travel from Khorda to Cuttack, Maa Mangala hotel, as shown in **Fig. 1.4.** without consideration of polluted area as a barrier and hence navigates to the highly polluted area but in **Fig. 1.5.** the driver requires 2 hours 15 minutes to cover that distance as he is considered the polluted area as barriers and followed the longest but healthiest path for a safe journey.

1.5 Conclusion and future work

The shortest distance may not be the best solution for smart city users every time. Some routes may cause severe health impacts while traveling. Hence, it is essential to identify the key features to determine the optimal path for smart city citizens. The presented proposed work based on geospatial science and cloud-based mapping service enables the user to generate network datasets and integrate spatial characteristics into the database to obtain such key routing parameters. This research was an attempt to find out the pollution exposure level at each route in Orissa. Therefore, It also used the EBK algorithm, which is the best suitable interpolation method for non-stationary data collected from unstructured sensors location than any other spatial interpolation technique to determine spatial correlation and spatial distribution of pollution level among those monitoring stations. Identification of the pollution level at each route is an efficient method for those patients who suffer from chronic diseases due to the high exposure of pollution. The final results of the work, which displays as the least polluted route in the designed web application, can be used by patients and any other smart city users to improve their health conditions. The proposed work has some limitations, which can be enhanced in our future work. The first and most critical issue is the number of active sensors available in Orissa, whose value can improve the performance of routing results. This work is limited to spatial analysis, which can be enhanced by Spatio-temporal analysis with a multivariate pollution dataset.

Acknowledgment

This research and product development work is financially supported by the IMPRINT (Grant No.-7794/2016), an initiative of Ministry of Human Resource Development, Government of India and Ministry of Housing and Urban Affairs, Government of India. The authors would like to thank once again.

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