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RESEARCH ARTICLE

Fuzzy Logic-Based Approach for Location Identification and Routing in the Outdoor Environment

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ABSTRACT Finding the precise and accurate location of devices on road networks is challenging in remote areas with poor internet connectivity and Global Positioning System coverage. Navigation applications that completely depend on the internet and reference spatial data for location identification and mapping do not perform well in case of frequent internet disconnection. These reference spatial data sources have many associated challenges like large size, errors in data, and restricted access. To address these challenges, this paper provides an approach for localization and routing using self-generated reference data using likelihood estimation. According to the proposed approach, the trajectory information is used to create the reference data in the format of Comma Separated Values (CSV). This reference data is first analyzed for quality issues and then used for navigation purposes. Further for the localization Sugeno Fuzzy Model is used as a fuzzy inference system for the initial localization and subsequent mapping of the location. The proposed approach is validated using an Android application on seven predefined routes. According to the performed result analysis, the proposed fuzzy logic-based approach is able to provide location identification with 98.9 percent accuracy with a root mean square error value of 3 percent.

INDEX TERMS Localization, location information, map errors, map matching, reference map, resource optimization, smart devices.

I. INTRODUCTION

The precise location of the user is important for many daily-use applications. These applications use the current location of the user to provide different location-based services that may range from basic direction information to many other business-oriented solutions. As per the current technological needs, navigation systems and location-based services make use of Machine Learning (ML), Augmented Reality (AR), and Virtual Reality (VR) to provide effective results to users [1]. Due to user-friendly interfaces, ease of use, and availability of required resources, mobile applications are becoming more popular. The effective use of the hardware of the mobile phone also promoted many ML-based mobile navigation applications [2]. Mobile phone-based applications use Global Positioning System (GPS) for location identification and are used to provide context-aware solutions [3], [4]. A typical navigation application consists of several components, including information sources, processing techniques, and output dissemination methods. Figure 1 provides a brief overview of the components of navigation applications. The information source is responsible for providing the location of the user, spatial information about the road network, motion information about the device, and some additional

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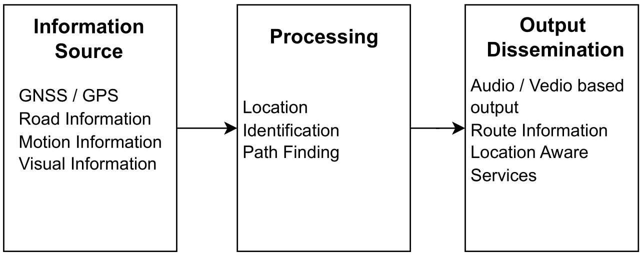

FIGURE 1. **Basic elements of the navigation application.**

visual information like reading from a camera, radar, or laser device. For location information, mobile applications use GPS/GNSS, cellular data, and sensor-based techniques. Google Maps, Bing Maps, OpenStreetMap, open-source applications, etc., act as sources of spatial information. Sensors and devices such as an accelerometer and gyroscope can be used to detect device motion. The processing unit of the navigation application comprises different algorithms and techniques for location identification and route finding. The output of the processing unit is further disseminated to different output modes of the application. These output modes include audio/ video-based output, location rendering on the screen, location-aware options, and route guidance features.

By considering various spatial and location factors for the device and map, localization techniques translate the user's input onto the digital map. Due to environmental factors, technology errors, and coverage area, the GPS receiver output has drift error from the actual user location, so map matching or localization techniques are used to minimize the drift error. These techniques allow GPS data to be mapped onto a digital map while taking into account various spatial and topological parameters [5], [6], [7]. Map matching algorithms are basic elements of the navigation application that are used to provide the mapping of user location on the digital road network by considering road type, the direction of movement, speed, distance, and other topological features [8]. In addition to the GPS data, the performance of map-matching algorithms is also dependent on the quality of the reference dataset which is a digital road network. Open source and non-proprietary reference datasets suffer from many quality issues and these quality issues further lead to poor navigation output [9], [10]. OpenStreetMap, being one of the crowdsourced projects, has many quality issues and for most of the underdeveloped areas these issues are uncertain [11], [12], [13]. Map matching algorithms are used to deal with errors or drift in location information rather than errors in reference data. To handle the errors in reference data, additional methods are required to be added to the navigation application. To solve these issues, this paper presents an approach that includes a map generation process, map matching, routing, and output rendering. In this approach, a fuzzy logic-based approach is used for map matching. In this process, fuzzy rules are designed for map matching. These rules are based on trapezoidal and triangular methods. Further, the fuzzy inference is implemented using the Sugeno inference model. The perpendicular distance between the GPS fix and road link, speed of the vehicle, heading error, Horizontal Dilution of Precision (HDOP), and head movement are considered for the fuzzy rule generation process. These parameters provide important information and environment for identifying the location of moving devices on the digital map. In addition to fuzzy logic-based map matching, this paper uses Comma Separated Values (CSV) file-based approach for reference data sets. This CSV-based approach reduces the space required for data storage. In brief following the major contribution of this research study:

- To overcome the challenges associated with the quality and size of reference spatial data, the paper proposes an approach to generate references using likelihood estimation.
- The generated spatial data is stored in CV files to reduce space requirements.
- The proposed approach provides GPS localization and routing Sugeno model-based fuzzy inference system. For this approach, 60 rules are designed using five input parameters.
- The proposed approach is validated using an Android application on seven predefined routes.

The introduction section of this research paper provides basic information about the navigation system, map-matching algorithms, and the dataset involved in the navigation process. Objectives of the paper are also provided in the introduction section. After the introduction section, section II provides a literature review that covers different research studies in the field navigation system and map matching algorithms. Different types of navigation systems and their brief information are provided in the literature section. Different map-matching algorithms and their features/challenges with respect to navigation applications are also presented in section II. Based on the introduction and studied literature, section III outlines the methodology of the proposed work. Section III covers basic terms related to navigation systems, standard algorithms used in the proposed study, the process followed to conduct the experiment, and the experiment itself. The process defined in the methodology section includes data preparation, location identification, and routing processes. The proposed algorithm, the used dataset, and performance matrices are also described as elements of the experiment in the methodology section. Section III-B1 provides the details of experimental results and analysis of obtained results with respect to identified performance and accuracy matrices. A comparison of performed experiments with other published research studies is also presented in section III-B1. Finally, the paper concludes with future scope and opportunities in section III-B2.

II. LITERATURE STUDY

This section contains information on the reviewed literature and the most recent advancements in navigational services and systems. Navigation services are made possible by the development of available handheld GPS devices. Navigation services depend on the user's location and provide a range of functions based on the location [14]. Provides details of literature on navigation systems and map-matching algorithms. There are two categories of navigation systems: indoor navigation systems and outdoor navigation systems. Indoor navigation systems are designed to assist people find their way inside buildings or other enclosed locations, whereas outdoor navigation systems, provide solutions for travel on a road network or other open regions. The three categories of outdoor navigation systems are map-based, map-less, and map-build-based [16], [17], [18]. Mapbuild-based systems are built on top of Simultaneous Localization and Mapping (SLAM) systems. Due to the lack of maps, the last 10 years have seen considerable progress in SLAM navigation systems. The SLAM system uses the camera's picture streaming, map data including sparse and dense information, a visual odometer, etc. for navigation. SLAM systems often employ a teach-and-repeat approach to operation [19]. The SLAM systems use the Bundle Adjustment (BA) method to locate objects using a camera and other visual components. The BA application for the SLAM system was the first to utilize the visual odometer. For both indoor and outdoor navigation, several different SLAM systems have been developed, including Oriented FAST and rotated BRIEF (ORB) SLAM, parallel tracking, and mapping (PTAM), and Square Root Unscented Kalman Filter (SRUKF) [20]. These systems perform operations like feature selection, extraction, mapping, localization, routing, and navigation [21], [22]. The convergence theorem, associative memory, fuzzy logic, and filters were also used in the SLAM system. These techniques were used to provide routing and localization to SLAM-based robots [23], [24], [25]. Topological information with sensor data is used to provide the maples driving [26]. A 3M (''multi-robot, multi-scenario, and multi-stage'') based architecture was created using reinforcement learning approaches to increase the precision of mapless navigation [27]. In order to offer the route in a scenario with no road information, a hidden Markov model with an ideal transition matrix was used. [28]. In an indoor environment, a fuzzy logic-based approach is used to control the movement of mobile robots [29]. Fuzzy logic-based systems are used in reliability analysis in ship navigations, indoor robot navigation, and route finding and traffic analysis in outdoor environments [30], [31], [32].

The research community provided various navigation and map-matching methods to improve the efficiency and precision of the mapping process. The map-matching process is divided into three types; named as geometrical, topological, and hybrid techniques. Geometrical map matching techniques use road node information and GPS positional information to provide the mapping results. Topological map matching techniques use the road node and topology information to provide the mapping of GPS fix onto the map. Hybrid map matching techniques combine the concept of geometrical or topological algorithms with some advanced techniques to provide mapping results [5]. According to previous research, the hybrid map matching algorithm uses the concepts of fuzzy logic, Kalman filter, Markov model, pattern matching, machine learning, and other techniques to provide the mapping of GPS fix onto the digital road network [7]. Fuzzy logic was designed to provide the mapping of qualitative data of deduced reckoning sensors and GPS devices [33]. Map matching of wheelchair routing was also implemented using the concept of fuzzy logic [34].

In recent years many different techniques were proposed by the research community and these techniques use trajectory information to provide the best matching result with minimum error [35]. In the category of hybrid techniques, many researchers used the concept of probability theory and machine learning to improve the accuracy of the mapping process. However, these techniques used speed, distance, and road information but these studies do not focus on human choice and signal errors [36]. Many map-matching techniques use vision-based data with GPS to improve the mapping accuracy, but these techniques require huge resource requirements to process the vision-based data. So, in the case of vision or image-based map-matching techniques, the huge storage requirement is also a challenging issue for the users [37]. According to recent studies, map matching algorithms with small-scale GPS data have good computation speed but are unable to provide good accuracy. The map matching algorithms require a long time to compute when dealing with large numbers of GPS data [38]. Therefore, new methods are needed to increase the precision and effectiveness of map-matching algorithms for high-frequency and large amounts of data.

The digital geographic data also affects the accuracy of the mapping process. In comparison to offline datasets, online geographical datasets have fewer errors [29]. To replace the shape files of the offline spatial dataset, a graph database was used with the OpenStreetMap dataset in the navigation process. In this method, a graph database is used to store the navigational information in the form of images. Selected images of the navigational region are mapped with location information. In this method, a user GUI is provided with images stored in the graph database [39]. Additionally, device cameras, markers, inertial sensors, and points of interest were used to reduce the requirement for storage for the navigation system [40].

The reviewed literature indicates that significant research is being conducted to enhance the performance and accuracy of navigation systems. The studied literature indicates that little effort has been put in to minimize the size of developing geographic databases. Additionally, the effects of voluminous storage on processing power and information presentation have not been fully examined. Moreover, only licensed proprietary systems have been able to integrate augmented reality with location tracking, and even these systems necessitate a significant amount of processing and storage to operate an efficient, reliable, and scalable navigation system with camera-based output aid was required, per the aforementioned observations. To handle the above-mentioned requirements, a fuzzy base navigation system is proposed in this research paper, and details of this system are explained in the subsequent sections.

III. METHODOLOGY

In this paper, we provided a navigation system using the concept of CSV file as a spatial dataset for the road data set. This system uses the concept of a fuzzy inference system localization of GPS data on a digital road data set. The working of the proposed navigation system is based on some basic terms. These terms are:

- Node: A node in the road network represents the location information. It is like a vertex of a graph data structure. The node comprises the longitude and latitude value of the position.
- Link: A link is a connection between two nodes. It is like the edge of a graph data structure. Combination of a link from road segment. Each link has some associated cost, and this cost can be in terms of distance or time.
- Route: Combination of nodes and edges from the route. The route is a traversal sequence of different nodes through edges.
- Trajectory: Trajectory is the recorded positional and temporal information using some GPS-based device.

A. STANDARD ALGORITHMS

This paper provides an approach to localizing the GPS receiver output and then routing on digital map data. The proposed approach utilizes an A-star algorithm and a fuzzy inference system to generate the output. A star (A∗) algorithm is used to identify the shortest route between two nodes. This algorithm uses the concept of best-fit search on edge weights [41]. Equation 1 shows the basic principle of the working of this algorithm.

$$Pathvalue\,(n) = \text{TotalCost}\,(i) + I\,(i)\,. \tag{1}$$

In equation 1; Pathvalue(n) is the total estimated cost of the path through node n, i is an intermediate node, TotalCost(i) is the cost from the start node to node I, I(i) is the heuristic value of the anticipated cost from node i to the destination node. A star algorithm expands its search using the value of Pathvalue(n). A Fuzzy inference system uses the concept of fuzzy logic to infer knowledge from input data and fuzzy rules. Figure 2 provides the basic working of the fuzzy interface system.

B. PROCESS

The suggested method uses the least amount of storage and computing resources to provide path information between the source and destination. Figure 2 depicts the system's fundamental part. Four fundamental subsystems, which are responsible for data preparation, location detection, path development, and the visual output component, enable this system to function.

1) DATA PREPARATION

This approach creates the spatial map data set using the concept of crowdsourcing. For crowdsourcing, the locations of the registered users are fetched to generate navigation reference spatial data (map). Volunteers can register on the MEN application for navigation purposes. Based on the consent of the users, the location information of the registered users is fetched for the data preparation. This component uses the trajectories of moving entities and basic map components. The map in CSV format for the routing process is created using this component. The GPS receiver output was used to retrieve the user's location data and also used to improve the data's quality.

We assume that there are n numbers of fixed POIs in the considered area. Let $P =< P_1, P_2, \ldots, P_m >$ (where $m \geq n$) be the POIs on the considered area. Each POI stores geometric and topological information about the point. Each POI location information is represented by $LI =< L_1, L_2, \ldots, L_K >$, where each L_j is a geometric or topological component for the location information for all $2 \leq j \leq K$, and K is a maximum geometric or topological component for any POI. To increase the accuracy of reference spatial data, GPS trajectories of different moving entities were considered. These trajectories include pedestrian data and vehicle data. Every entity has different trajectory data based on moving behavior and GPS. So, data of each entity corresponding to a particular POI is represented by $T =< T_1, T_2, \ldots, T_u >$, such that $u \geq 1$ and each T_u is geometric or topological information of ith entity for particular POI. Trajectory data of each entity at each POI typically provides different values and exhibits fluctuations. Figure 3 shows the trajectory information of four different entities at six POI. Fluctuations in location information are due to GPS receiver delay, sampling rate, and moving speed. Trajectory readings from a different moving entity (GPS receivers) at a particular POI follow Gaussian distribution so T_u (trajectory information) at every P_i (POI) using a Gaussian distribution $G\left(\mu_{iu}, \sigma_{iu}^2\right)$ where μ_{iu}, σ^{2iu} are mean and standard deviation respectively. We assume that the final calculated readings from different trajectories at POI P_i are $< F_1, F_2, \ldots, F_r >$ then mean and standard deviation using Gaussian distribution is calculated and shown using equations 2 and 3 respectively.

$$\mu_{iu} = \frac{1}{r}\sum\nolimits_{v=1}^{r} F_v \tag{2}$$

$$\sigma_{iu}^2 = \sqrt{\frac{1}{r-1}\sum\nolimits_{v=1}^{r}\left(F_v - \mu_{iu}\right)^2} \tag{3}$$

Using the Gaussian distribution function and equations 2 & 3 we finalized the position value of POI for the map and further this POI information with topological information retrieved from movement trends was used to create the links or connections between different POIs. While finding the route, the location can be estimated using maximum likelihood estimation. Likelihood estimation for LE_{if} (i_{th} POI) calculated using $G\left(\mu_{iu}, \sigma_{iu}^2\right)$ can be estimated using Gaussian distribution and is shown in equation 4. The maximum

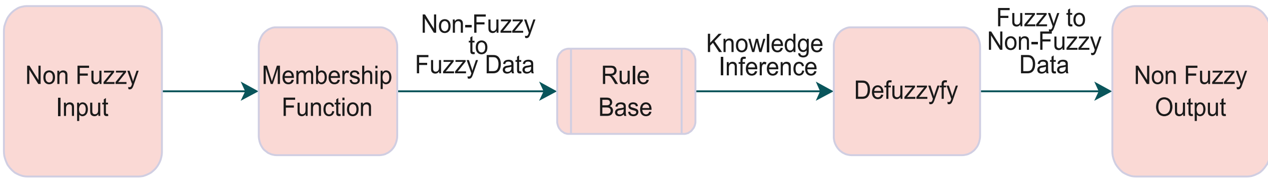

FIGURE 2. **Steps involved in the working of the fuzzy inference system.**

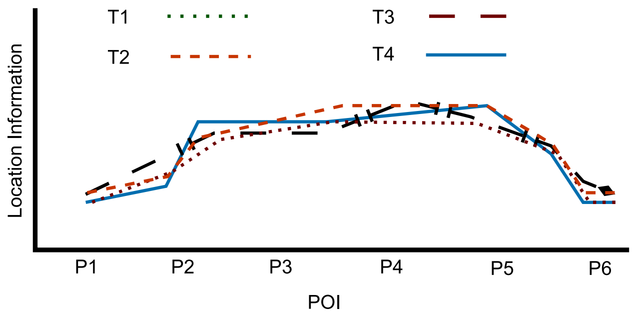

FIGURE 3. **Sample scenario of captured four different trajectories corresponding to six POIs.**

likelihood distance is 10 meters.

$$\xi_{iu}\left(LE_{if}\right)=\frac{1}{\sqrt{2\pi\sigma_{iu}^{2}}}e^{-\frac{(LE_{if}-\mu_{iu})^{2}}{2\sigma_{iu}^{2}}} \tag{4}$$

If $\xi_{iu}\left(LE_{if}\right)$ has mapped to many different POIs, the final reading can be obtained using equation 5 and the final sampling position can be obtained using equation 6.

$$\xi_{u}\left(LE_{f}\right)=\prod\nolimits_{i=1}^{m}\xi_{iu}\left(LE_{if}\right) \tag{5}$$

$$u^{*}=\arg\max_{u\in T}\xi_{u}\left(LE_{f}\right) \tag{6}$$

Using this process, we saved map data in the form of CSV format to use as reference spatial data for navigation purposes.

2) LOCATION IDENTIFICATION

This component processes GPS receiver data that could drift somewhat from the actual location due to transmission errors and latencies. A fuzzy inference system is used to provide the mapping of GPS information on the map nodes. The location identification process uses 5 input parameters to provide the mapping of GPS fix onto the road network. These parameters are 1) perpendicular distance between GPS fix and road link, 2) speed of the vehicle, 3) heading error and which is identified as the difference between vehicle movement direction and road direction, 4) Horizontal Dilution of Precision (HDOP) related to GPS signal errors, 5) head movement. In considered fuzzy logic-based location identification, these 5 input parameters are used for the fuzzification process (i.e. conversion of non-fuzzy data to fuzzy data). The trapezoidal method defines the membership of data based on the upper and lower limits of the data value and the support value, while the sigmoidal method uses two parameters, the slop and crossover point, to define the membership. The slope is defined by the lower data value, and the crossover is defined by the support value. A sigmoid membership function is preferred for continuously distributed data values. The sigmoid method provides an even and steady transition between membership levels. The trapezoidal method is simple and effective for discrete data values. The trapezoidal method is used for variables that have discrete boundaries. So as per the studied literature, in the considered scenario, speed, and distance are continuous values, so sigmoid membership is used, whereas for HDOP, heading error, and head movement, a trapezoidal membership function is used. is used. Speed and perpendicular distance follow steady transitions, so the sigmoid method is used to capture the gradual change in these parameters. Heading error and HDOP are typically bounded by certain ranges, so the trapezoidal method is used for HDOP, Heading error, and Head direction.

The sigmoid method as shown in Figure 4 is used for the fuzzification of speed and perpendicular distance. Similarly, the trapezoidal method as shown in Figure 5 is used for the fuzzification of heading error, head direction, and HDOP. In Figure 5, heading errors have four values zero, small, medium, and large so the heading error graph shows the trapezoidal plot of all four values. Whereas head movement and HDOP both have two values, and their graphs show trapezoidal growth based on their values. The fuzzy subsets associated with distance, speed, heading error, head direction, and HDOP have 4, 5, 4, 2, and 2 membership values, respectively. The values of fuzzy subsets for the first input (that is, distance) are very small (0 m), small (greater than 0 m and less than 3 m), medium (greater than 3 m and less than 10 m), and large (greater than 10 m). Beyond 20-meter distance is considered invalid. The values corresponding to fuzzy subsets of the second input (speed) are zero (0 KM/H), low (greater than 0 KM/H and less than 30 KM/H), medium (greater than 30 KM/H and less than 50 KM/H), high (greater than 50 KM/H and less than 80 KM/H), and very high (> 80 KM/H). The values of fuzzy subsets for heading error are zero (1 degree), small (greater than 1 degree and less than 20 degrees), medium (greater than 20 degrees and less than 40 degrees), and large (greater than 40 degrees). The values of fuzzy subsets for head direction are the same and opposite. This is based on the direction of the road link and the direction of the vehicle. The values of fuzzy subsets in HDOP are small (value less than 25) and large (value greater than 25).

The fuzzy inference system working is based on the inference rule. These inference rules are based on the fuzzy membership function, the values of the fuzzy subset for membership, and the target output. In this experiment,

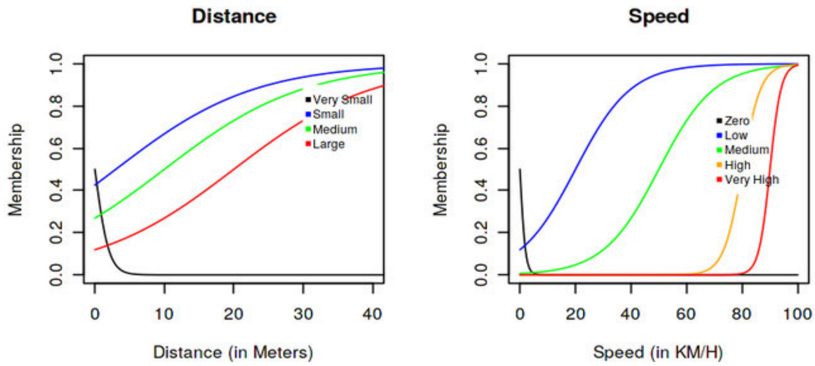

FIGURE 4. Fuzzification of distance and speed using sigmoid membership.

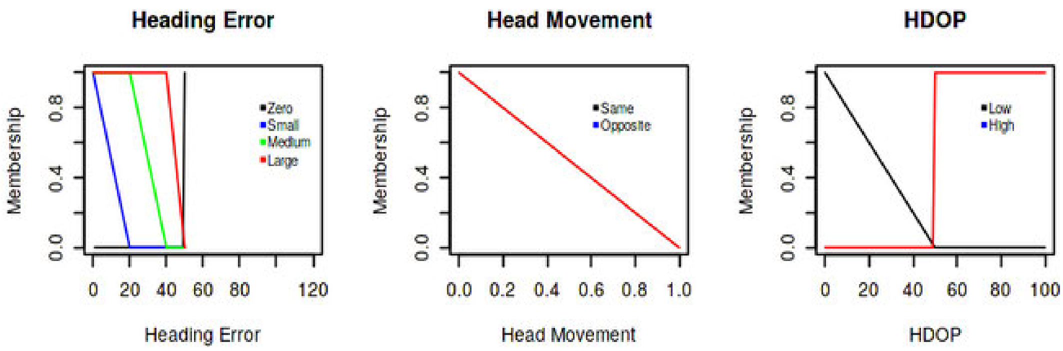

FIGURE 5. Fuzzification of heading error, head movement, and HDOP using trapezoidal membership.

we considered five membership functions and seventeen values corresponding to fuzzy functions, so as per the next step of this fuzzification process, rules were designed using the Sugeno Fuzzy Model. The output of each rule is location identification, and this output (mapping output MO) is defined using 3 fuzzy values: low, medium, and high. Based on the recommendation of previous research, fuzzy inference rules were designed using knowledge engineering and a weighted score of membership function. The weight was assigned to each membership function, and based on the weight and variable values, inference rules were designed. The map localization process has two aspects: one is localization at the beginning of navigation (known as an ''initial fix''), and the second is localization during navigation. A total of 48 rules were designed and added to the rule base. Apart from these 48 rules, 12 rules were defined for the initial fix because the initial fix process has different scenarios in comparison to localization during navigation. These 12 rules were used to map the GPS fix on the map at the beginning of the navigation process. From the considered input parameters high priority is given to perpendicular distance and heading error. The fuzzy inference process with the weighted sum operator uses these rules to extract the mapping output. Sample rules are as below.

- *If (speed is low) and (distance is medium) and (heading error is large) and (head movement is opposite) and (HDOP is low) then (output is medium)*
- *If (speed is low) and (distance is small) and (heading error is small) and (head movement is same) and (HDOP is low) then (output is high)*
- *If (speed is high) and (distance is large) and (heading error is small) and (head movement is opposite) and (HDOP is high) then (output is low)*
- *If (speed is low) and (distance is large) and (heading error is Medium) and (head movement is same) and (HDOP is large) then (output is low)*
- *If (speed is high) and (distance is small) and (heading error low) and (head movement is same) and (HDOP is low) then (output is medium)*

Based on the designed 48 mapping rule, Table 1 shows the fuzzy association values of input parameters and output values. In Table 1-4, the values of input parameters are abbreviated as; Medium: M, Low: LO, High: H, Large: LA, Very Large: VL, Small: SM, Very Small: VS, Zero: Z, Same: SA, Opposite: O. The fuzzy association values for 12 initial mapping rules are shown in Table 2. Table 1 and 2 shows the association values and mapping outcome corresponding to selected values of input parameters.

The fuzzy association values between two input parameters are shown in Tables 3 and 4. Table 3 shows the fuzzy association matrix for distance and speed. This matrix shows the mapping output based only on the different values of speed and distance. Similarly, table 4 shows the fuzzy association matrix of distance and head direction. Tables 3 and 4 show values mapping output corresponding to different combinations of values of input parameters. The combined fuzzy

TABLE 1. Fuzzy association values of selected input parameters according to defined rules for the mapping process.

Fuzzy Parameters / Rules	Distance	Speed	Heading Error	Head Direction	HDOP	Output
1	M	LO	LA	O	LO	M
2	SM	LO	SM	SA	LO	H
3	LA	H	SM	O	H	LO
4	LA	LO	M	SA	LA	LO
5	SM	H	LO	SA	LO	M
6	VS	LO	Z	SA	LO	H
7	VS	Z	Z	SA	LO	H
8	VS	M	Z	SA	LO	H
9	VS	H	Z	SA	LO	H
10	VS	VH	Z	SA	LO	H
11	VS	Z	SM	SA	LO	H
12	VS	M	SM	SA	LO	H
13	VS	H	SM	SA	LO	H
14	VS	VH	SM	SA	LO	H
15	SM	LO	Z	SA	LO	H
16	SM	Z	Z	SA	LO	H
17	SM	M	Z	SA	LO	H
18	SM	H	Z	SA	LO	H
19	SM	VH	Z	SA	LO	H
20	M	LO	Z	SA	LO	H
21	M	Z	Z	SA	LO	M
22	M	M	Z	SA	LO	M
23	M	H	Z	SA	LO	M
24	M	VH	Z	SA	LO	M
25	LA	LO	LA	SA	H	LO
26	LA	LO	M	SA	H	LO
27	LA	M	M	O	LO	LO
28	LA	H	M	SA	H	LO
29	LA	VH	M	O	H	LO
30	SM	LO	H	SA	H	M
31	SM	Z	SM	SA	LO	H
32	SM	M	SM	SA	LO	H
33	SM	H	M	SA	LO	H
34	SM	VH	LA	SA	H	M
35	M	LO	LA	O	H	M
36	M	Z	LA	O	LO	M
37	M	M	LA	SA	LO	M
38	M	H	M	SA	LO	M
39	M	VH	LA	O	LO	LO
40	LA	LO	Z	O	LO	LO

TABLE 1. *(Continued.)* Fuzzy association values of selected input parameters according to defined rules for the mapping process.

41	LA	LO	M	SA	LO	LO
42	LA	M	M	O	LO	LO
43	H	VH	L	O	H	LO
44	H	H	M	O	H	LO
45	S	M	Z	SA	LO	H
46	S	VH	SM	O	H	M
47	S	LO	SM	SA	LO	H
48	M	M	M	O	LH	A

TABLE 2. Fuzzy association values of selected input parameters according to defined rules for the initial mapping process.

Fuzzy Parameters / Rules	Distance	Speed	Heading Error	Head Direction	HDOP	Output
1	VS	Z	Z	SA	LO	H
2	SM	Z	LA	SA	LO	H
3	M	Z	M	SA	LO	A
4	LA	Z	LA	SA	LO	LO
5	VS	Z	Z	O	H	A
6	SM	Z	LA	O	H	LO
7	M	Z	M	O	H	LO
8	LA	Z	LA	O	H	LO
9	VS	LO	Z	O	LO	A
10	SM	LO	LA	O	LO	A
11	M	LO	M	SA	H	A
12	LA	LO	LA	SA	H	LO

TABLE 3. Fuzzy association matrix for distance and speed.

Distance / Speed	VS	S	M	LA
Z	H	H	M	M
LO	H	H	LO	LO
M	H	H	LO	LO
H	H	M	M	LO
VL	H	M	M	M

association matrix of all input parameters using membership value and weight factor is shown in Table 5. In Table 5, all input parameters with different membership values are considered to define the outcome.

Based on the above-defined rules, the selected nodes of the road network were processed for each GPS fix using the fuzzy

TABLE 4. Fuzzy association matrix for distance and head direction.

Distance / Head Direction	VS	S	M	LA
S	H	H	M	LO
O	M	LO	LO	LO

TABLE 5. Fuzzy association matrix of input parameters based on membership value and associated weight factor.

	Distance	Speed	Heading Error	Head Direction	HDOP	Output
Distance	1	0.6	0.45	0.6	0.45	0.62
Speed	0.6	1	0.35	0.5	0.35	0.56
Heading Error	0.45	0.35	1	0.35	0.2	0.47
Head Direction	0.6	0.5	0.35	1	0.35	0.56
HDOP	0.45	0.35	0.2	0.35	1	0.47
Output	0.62	0.56	0.47	0.56	0.47	0.536

inference process. MO corresponding to selected road nodes is de-fuzzify using the reverse membership functions. In this experiment, the Mean of Maximum (MOM) method is used to calculate the crisp set from the fuzzy output. The discourse universe consists of the nodes of the road network. These nodes are retrieved from the CSV file. For the MOM method, the weight factor is given to all parameters. The weightage given to distance, speed, heading error, Head Movement, and HDOP are 70, 50, 20, 50, and 20 respectively. The best node is selected as the mapping result of the GPS fix. This output is used in the routing process to identify the direction of movement and the next node. This weightage is also used to compute output in Table 5.

3) ROUTING

For navigation from one location to another location, it's mandatory to have a route. This component uses the A star algorithm to find the route between two locations.

Let $P =< P_1, P_2, \ldots., P_n >$ be the n number of nodes of the considered map (graph). A star algorithm generates a minimum cost path between two nodes by considering intermediates nodes using the weight function shown in equation (7).

$$F(P_i) = s(P_i) + d(P_i) \tag{7}$$

where P_i is ith node to be considered for the path between and source and destination and $P_i \in (P =< P_1, P_2, \ldots., P_n >)$. $s(P_i)$ is the calculated cost to traverse the path between the start node and (P_i). $d(P_i)$ provides an estimation of the cost to traverse a path from P_i node to the destination. In the considered experiment distance is considered as cost matric and the cost of the shortest path is only dependent on the distance between source and destination. The output of the localization step is used in routing for the route and direction estimation.

C. PROPOSED SYSTEM

The proposed system provides a route between two positions by considering the location of the user as GPS output. This system generates mapping output of GPS fix on the road network with minimal storage requirements. Offline navigation systems primarily use shape files and data files for navigation purposes. These shape files (.shp and.shx) require good storage requirements on the navigation device. To optimize the storage required, the proposed system uses a comma-separated file to store the positional information of the road network, and the GUI to this system is provided by using the device camera. The fuzzy inference system (Sugeno Fuzzy Model) is used to map the GPS fix (localization) onto the road link. For example, at a given time, the system fetches GPS receiver output (lat. x, y, lon. y), device direction (orientation: O degree), and speed (s KM/H). This information is used to identify the HDOP, heading error, head direction, and perpendicular distance with respect to available road nodes in the vicinity. Based on the calculated distance, Sugeno Fuzzy Model with a weighted sum operator is applied and output is calculated. Calculated outputs were processed using an aggregation and defuzzification procedure to identify the strength of the output. A node with the highest level of confidence in its mapping is considered the localization output.

A star algorithm is used to provide the shortest distance between the considered node and the end node. After every GPS fix mapping, A star algorithm is used to update the route between the start and end node by considering the recent GPS fix. Algorithm 1 provides details working of this system.

The proposed system was implemented and verified using the real-time road network dataset. A Mobile phone-based application was developed to validate the proposed system. Data was collected using the Android application and further, that data is processed and converted to CSV format. The GPS data collection interval was 10 seconds. For this study information from seven routes (shown in Table 6) was used. Built-in GPS and GLONASS modules of the mobile phone were used to receive the GPS points.

The proposed system was examined based on execution time, accuracy, and space requirements. The accuracy of the mapping process for the navigation system can be calculated by identifying the percentage of correctly mapped locations (as shown in Equation 8). Similarly, Root Mean Square Error (RMSE) metric is used to calculate the error rate in the mapping process.

$$Accuracy = \frac{Total\ number\ of\ matched\ nodes}{Total\ number\ of\ nodes\ considered} \times 100 \tag{8}$$

If $T =< T_1, T_2, \ldots., T_u >$ are the input points to process and SD$=< SD_1, SD_2, \ldots., SD_u >$ are the actual locations,

Algorithm 1

Input: Road data (D) comprises N nodes and Link information (L). Fuzzy inference system with membership functions, rule-based, and rule for defuzzification. Start node ns and end node ne.

Output: Route from source to destination

Function (D, ns, ne)

{

do

Take the output of the GPS receiver f_i

If (f_i*is a first observation)*

Identify heading error, speed, the perpendicular distance

Perform fuzzification on input

Perform mapping according to 12 fuzzy rules of initial mapping

Generate the shortest path (P) using A star

Else

Consider nodes according to the previously mapped node and path P

Record heading error, speed, perpendicular distance, HDOP, and head movement using f_i*and selected road nodes*

Apply fuzzification

Extract information using fuzzy rule-base

Perform defuzzification

Select the best node and map the GPS fix to that node

Use A star to recalculate SP by considering the recently mapped node and ne

While (f_i*!= ne)*

}

TABLE 6. Route Specification.

#	Route Length (in KM)	Location (latitude, longitude) of the start and end point of the route in degrees
1	0.3	(30.516913,76.660170)(30.514242,76.660846)
2	0.87	(30.512529,76.658809)(30.517021,76.660418)
3	6.94	(30.518102,76.659014)(30.487103,76.603009)
4	16	(30.281446,76.835677)(30.335909,76.834534)
5	34.5	(30.515920,76.6583429)(30.258633,76.856209)
6	42.9	(30.257539,76.852845)(30.478197,76.578406)
7	60.3	(30.173239,76.861614)(30.532606,76.678967)

then the formula for RMSE is given in equation 9.

$$RMSE = \sqrt{\frac{1}{u} * \sum\nolimits_{i=1}^{u} (SD_i - T_i)^2} \tag{9}$$

The space requirement of the proposed system is calculated by identifying the storage requirements on the secondary storage. The execution time of the navigation process is calculated using equation 10. It includes the total time elapsed by an algorithm to generate the results.

$$\text{Total Execution Time (TT)} = \text{ET} - \text{ST} \tag{10}$$

FIGURE 6. Considered Map.

FIGURE 7. Device orientation and output of designed application during the experiment.

For equation 10, ET and ST are the start and end times respectively.

IV. EXPERIMENTAL RESULTS

We employed mobile devices in an outdoor road environment to assess the performance of the proposed solution in real time. The map of the considered area for the experiment is shown in Figure 6. The mobile device was kept in position during the experiment in such a way that its X-axis was parallel to the forward direction and its Y-axis was perpendicular to the X-axis on the right side (as shown in figure 7). The output of the application is displayed in Figure 7. The experiment involved mounting the mobile device on both a car and a bike. Figure 6 illustrates the output of the mobile application when the device was mounted on a bike. Five separate users or volunteers carried out the experiments repeatedly on 7 predetermined routes (as shown in Table 1). Distance travelled by user 1 to user 5 are 60.6, 23.2, 24.15, 69.45, and 64.85 KM and the considered map is shown in Figure 6.

By assessing the experimental data obtained from considered users, the accuracy and RMSE of the location identification process were calculated. An average RMSE of 7.5 percent and an accuracy of 97.74 percent were noted. The analysis of the accuracy and RMSE attained by five users is shown in Figure 8. The analysis presented in Figure 8 shows that the minimum accuracy value was reported to be 97 percent with an RMSE value of 0.096 points (0.9 percent), and the highest accuracy recorded is 98.9 percent with an

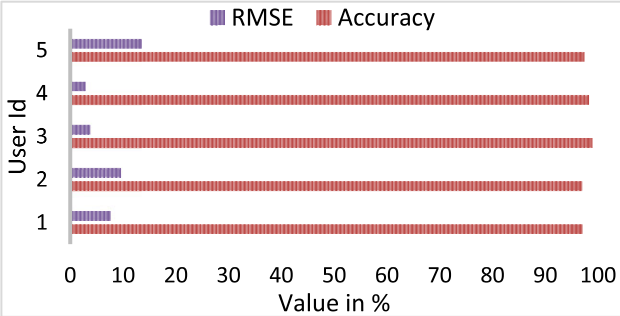

FIGURE 8. Analysis of recorded RMSE and accuracy achieved by 5 different users.

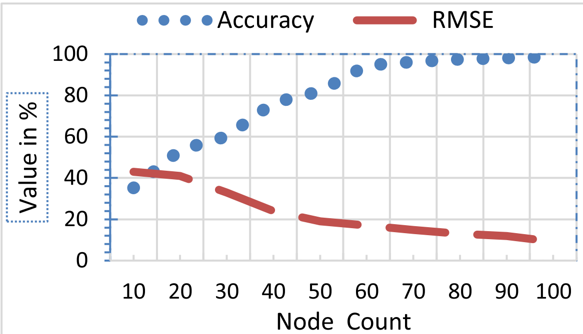

FIGURE 9. Impact of node count on accuracy and RMSE analysis.

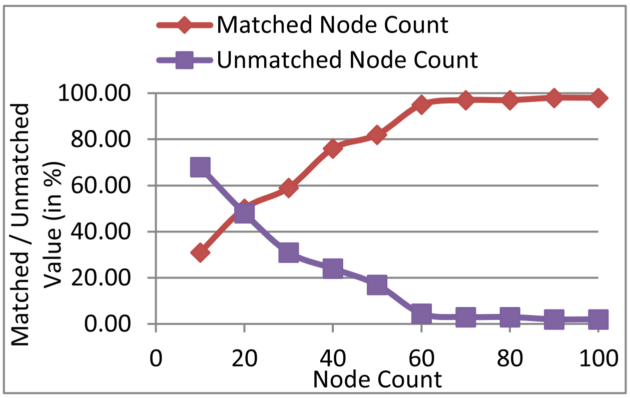

FIGURE 10. Analysis of the proposed system accuracy based on MaUC vs. Node.

RMSE value of 0.038 points. The observed RMSE error values ranged from 0.136 to 0.029 points.

We carried out the experiment for roads with nodes in the range of 10–100 with a GPS sample rate of 10 sec in order to examine the effects of road node density on mapping accuracy and RMSE. Figure 9 shows the impact of node count on accuracy and RMSE analysis. Similarly, figure 10 shows the impact of road nodes on the matched and unmatched node count. According to this analysis, if the numbers of nodes are very less then the system has very poor accuracy and a high error rate. For good accuracy, the system must possess sufficient nodes and the density of nodes should also be appropriate.

The highest accuracy to map 30 GPS points for the 300 meters track was 98.7%, and the minimum accuracy was 35.2%. Similarly, RMSE has a value in the range of 0.43 and 0.092. In the case of a road with a sparse node set,

TABLE 7. Space requirement to store road data set using CSV format and OSM format.

Route No	Storage space in Kilo Bytes OSM Format (All File)	CSV Format
1	163	18
2	215	19
3	2307	28
4	5871	80
5	3215	47
6	9832	123
7	10114	138
8	11923	170
Total	43640	623

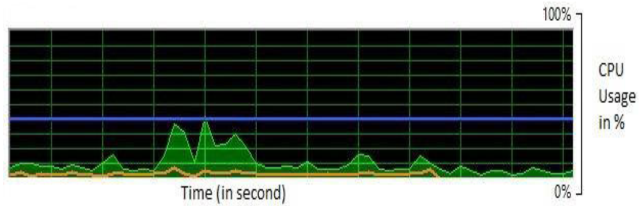

FIGURE 11. CPU utilization of OSM-based application.

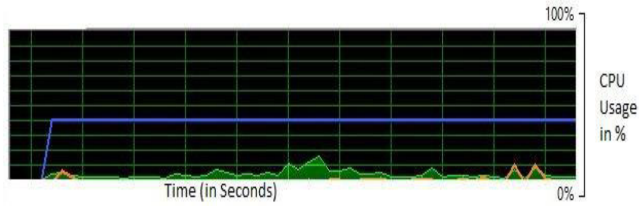

FIGURE 12. CPU utilization of the proposed navigation system.

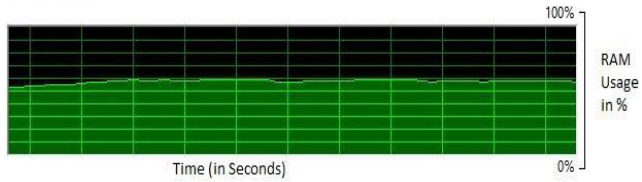

FIGURE 13. RAM utilization of OSM-based application.

the GPS fix might be mapped to nodes far away from the actual location. It leads to wrong mapping and causes low accuracy and high error value. Similarly, if a road network has a dense node set then the GPS fix would have many nodes to be mapped and it leads to correct mapping. The dense dataset also causes poor performance issues due to the processing of a large number of nodes. When we increase the node density, it doesn't increase accuracy; instead, it has unintended effects and negative performance effects. The route must contain a sufficient number of nodes for accurate mapping. Fewer nodes that are significantly apart from one another on the track lead to incorrect mapping and poor matching results.

A statistical analysis of route space requirements using CSV format was conducted with OpenStreetMap to demonstrate the usefulness of the CSV file-based data storage technique for navigation. The results are presented in Table 7.

To analyze the CPU and memory (RAM) utilization of the proposed system, Android Debug Bridge with the dump sys tool was used on the Windows operating system. Dumpsys is a command-line tool in the Android operating system.

TABLE 8. Comparison of the proposed technique with other published research papers.

Algorithm	Accuracy	Error	Key features	Ref.
Oriented FAST and Rotated BRIEF(ORB)-SLAM	Approximate 93%	In the best-case scenario error rate is 1.59 meters.	Uses feature extraction detection technique is used to identify the path and tracking. Based on the image dataset.	[43]
GraphiumMM	Approximate 93%	In the best-case scenario, the RMSE value is 12%.	Localization and routing were based on graph components, road information, and topological features were	[4]
AR-based Navigation	99 percent for indoor environment	In the average case scenario error rate is 4%.	Augmented reality, device camera, and SLAM were used for navigation and localization purposes	[44]
On-Board Diagnostics data-based Map Matching	97.45% percent accuracy.	In the best case error rate is very less which is approximately 3%.	Combination of weight and probabilistic-based map-matching algorithms. The experiment was conducted on low-sampling data.	[45]
Transfer learning approach for map matching.	97.1% and 95.4% for segment identification and point identification respectively	The error rate is depending on the considered dataset.	931 trajectories of road data were used for deep learning-based map-matching model	[46]
Proposed Approach (road-based localization and routing for crowdsourced data using an integrated fuzzy logic-based approach)	Maximum and minimum accuracy of 98.7% and 96%	In the best case and average case scenario, RMSE values are 9.2% and 11.7% respectively.	The special crowdsourced-based dataset is created for navigation purposes. A fuzzy logic-based model is used for map matching. A star algorithm is used for the route-finding process.	

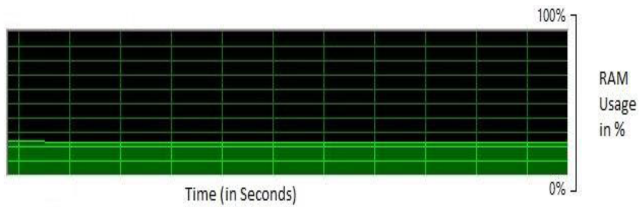

FIGURE 14. RAM utilization of the proposed system.

This tool provides comprehensive details about the system services and components that are active on an Android device. This tool along with Android Debug Bridge (ADB) gives users to access the system statistics and information, like window manager settings, battery life, sensor data, network status, memory consumption, CPU utilization, memory allocation, network statistics, and other performance matrices. While identifying the CPU and memory utilization, all other applications except system services were stopped. Figures 11 and 12 show the CPU utilization trends of OSM-based navigation application and proposed navigation system respectively. Figures 11 and 12 demonstrate the highest achievable CPU frequency (using the blue line) along with the actual CPU utilization in the green area. According to this analysis, the maximum recorded CPU utilization for the OSM-based application and proposed system were 38 percent and 12 percent respectively. The proposed system requires 32 percent less CPU utilization in comparison to the traditional method. Memory utilization OSM-based applications and the proposed system are shown in Figures 13 and 14. Maximum recorded memory (RAM) utilization for OSM-based applications and the proposed system were 61 percent and 26 percent respectively. The proposed system requires 43 percent less memory than OSM-based systems. So, the proposed system can work on a device having less processing power and memory. Table 8 compares the proposed technique with a few state-of-the-art approaches.

V. CONCLUSION AND FUTURE SCOPE

Mobile devices have become a vital part of our lives, almost all desktop-based tasks can be performed using a mobile phone. Road navigation is one of the major applications of mobile phones. To perform navigation either offline or online navigation services are required. Due to the huge requirement of space or processing, some mobile phones are unable to execute navigation applications. In this study, a novel navigation system was proposed that uses the idea of a CSV file as a source of spatial data. In this study, we proposed a navigation system that optimally uses device storage space, memory, and processing devices. In this system, heavy spatial files were replaced with CSV files. These CSV files were created using the concept of crowdsourcing and comprise only the positional information of the road network. In the next step, the localization process was implemented using the fuzzy inference system. A total of 60 rules (12 for initial mapping and 48 for other subsequent mappings) using five input parameters named; distance, speed, HDOP, heading error, and head direction were designed for the rule base. The working of the localization process depends on the designed fuzzy associative matrix. The rule base and fuzzy association matrix were used to map the GPS fix with road work. In addition to this, the path between the source node and the destination node was calculated using an A star algorithm. The device camera was used to provide the user interface. Further, the accuracy and performance of the system were evaluated using a case study. 8 different roads of cumulative length of 165.5 KM were considered for the experiment. From the result analysis, the proposed system was found to attain a maximum accuracy of 98.7% with a minimal RMSE of 0.09. Apart from this, the proposed system in comparison to the OSM-based application requires 43 percent less memory and 32 percent less CPU. The current study can be expanded in several ways to further enhance map-matching and navigation performance. In the future, the data creation process can be improved by using better likelihood techniques. Similarly, speed and direction of movement can also be considered in the data generation phase to increase the accuracy of the spatial database. In addition to this, in the future, this system can be enhanced using a better data collection approach and sparse dataset.

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