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Motion Control Bayesian Neural Visual Odometry Intelligent Routing For Traffic Management In Wireless Network

Dr. UMA S*
Department of Computer Science, Government Arts and Science College, Tirupattur- 635 901, Tamil Nadu, India

AMIRTHAVARSHINI R U
Department of Computer Science and Engineering, Rajalakshmi Engineering College, Thandalam, Chennai -602 105 Tamil Nadu, India

Abstract : *Machine Learning has massive influence in the automotive industry whichleads to evolution of intelligent routing for traffic management in wireless network via autonomous vehicles(AVs). The evolution of numerous automotive platforms for efficient traffic management has been the current trend.A method called, Bayesian Neural Visual Odometry and Polynomial Regression (BNVO-PR) with vehicle to vehicle communication for traffic management ensuring intelligent routing for autonomous driving is proposed. This method has three sections, namely, perception, localization and prediction.Spatio-Temporal Motion Control-based Perception is applied to the raw Udacity Self Driving Car dataset provided as input to obtain robust point of interest object detection with which intelligent routing can be ensured. Second, the obtained point of interest results are subjected to Bayesian Neural Visual Odometry-based Localization, ensuring computationally efficient object recognition for significant traffic management. Finally, with the recognized objects obtained, Polynomial Regression-based Autonomous Vehicle Prediction is designed to interpret actuate kinematic maneuvers in AVs, ensuringintelligent routing for efficient traffic management in wireless network concurrently. There is a reduction inrouting overhead and performance evaluation like precision, routing accuracy and routing time during autonomous driving using our network when compared with the existingmethods, leads to higher routing accuracy during inference, achieving accurate autonomous driving.*

Keywords: Bayesian Neural Network, Visual Odometry, Localization, Polynomial Regression

1. INTRODUCTION

Research and development in the domain area of machine learning lead to several discoveries and practical applications in distinct domains. The domain area where machine learning has an immense influence is the automotive industry and the evolution of extensively autonomous vehicles. Solutions with machine learning are utilized in several autonomous vehicles for performing localization and mapping in a simultaneous manner, sensor fusion and route planning. In analogous with full autonomy of commercial vehicles, the evolution of numerous automotive platforms is found to be the current trend.

Multiservice offloading and allocation mechanisms present fascinating challenges in the prevailing and next-generation vehicle networks. These mechanisms are data-centric that focus to utilize heterogeneous data inputs to identify optimal solutions. In the context of autonomous vehicles AVs, these mechanisms generate an

* - Corresponding Author : Dr. **UMA S**, *Department of Computer Science, Government Arts and Science College, Tirupattur- 635 901, Tamil Nadu, India*

exponential amount of time and deal as far as small and medium scale networks are concerned.

An Optimal Virtual Edge Autopilot Placement (OVEAP) algorithm employing Deep Reinforcement Learning (DRL) techniques to learn the behavior of exact optimization algorithms with the purpose of improving the network operators Quality of Service (QoS) and satisfying requirements of Autonomous Vehicles (AVs) was presented in [1]. By employing DRL algorithms not only resulted in the improvement of AVs service offloading but also ensured resource optimization significantly. Also, with the aid of OVEAP algorithm employing Integer Linear Programming (ILP) improved total edge server utilization with minimum allocation time.

As far as self-driving cars are concerned, ground detection is considered as an essential part of the perception system. The ground detection here is considered as a drivable area that is said to be textured and smoothly differentiated between adjoining areas, possessing certain common imperfections, including shadows and different light intensities.

In [2], RoadSegNet employing deep neural network architectures was proposed. With this method, accuracy was found to be improved significantly. As far as the world health organization (WHO), 1.3 million people are said to be killed in road accidents and 50 million people are said to be injured every year. Numerous methods and mechanisms have been designed for making driving safer, like introduction of advanced driver assistance systems (ADAS), intelligent transportation systems (ITS) and so on.

ITS with the recent technological advancements in communication systems have in turn paved the way for AVs deployment.Employing multi-agent reinforcement learning (MARL) algorithms, several research professionals have made a great deal of attempts in designing AVs and their recent advancements were proposed in [3]. Concentric efforts on handling decision-making by introducing mixed traffic with or without social-desirable AVs. However, careful consideration of scene still remains the major aspects to be included.

In [4], a review of vision-based semantic segmentation techniques was investigated. However, the resources involved in the design were not focused. To address on this aspect, machine learning components were analyzed in [5] for AVs therefore paving way for critical system behavior identification. With the speedy process of urbanization, an increase of private cars has restored buses as efficient means of transportation for general public that in turn results in the periodic eventuality of urban traffic congestion. With the ceaseless evolution of the Internet of Things (IoT), big data, and machine learning techniques, in supplementary to conventional manual private cars, autonomous cars have made an appearance. As a result, intelligence and network security in the area of transportation have become the focal point of several scholars in related fields.

System prediction and safety performance of Digital Twins (DTs) of autonomous cars on the basis of AI technology with the evolution of intelligent transportation in smart city was designed in [6]. Safe driving of autonomous cars was first taken into consideration and then, convolution neural network (CNN) was adopted. Finally, prediction model designed was made on the basis both load balancing and spatial-temporal graph convolution network for improving message delivery rate with high rate of security.

Yet another work to improve vehicle safety on the basis of the vehicle lateral active collision avoidance mechanism, collision avoidance technique, decision-making, and path planning and collision avoidance were designed in [7]. A deep deterministic policy gradient (DDPG) method to solve the control issue of automatic driving by designing reasonable reward function was presented in [8]. However a design of intelligent routing for traffic management in wireless network for AVs still remains major concern to be addressed. Therefore, our goal is to develop the right machine learning technique that can achieve acceptable routing accuracy, the successful autonomous driving in a representative track, but which operates in real-time within time and minimal overhead of its target automotive platform. In order to achieve this, the approach we took was to split the overall process into intelligent routing and traffic management that can be used for autonomous driving. The general workflow to identify an appropriate model is to first, design intelligent routing model with which the point of interest of AVs can be obtained in a precise manner. Following which, traffic robust and smooth traffic management is made therefore reducing the congestion significantly. In summary, the contributions of the method proposed in this paper are:

- The conventional perception model is modified by employing Spatio-Temporal Motion Control and used both the spatial and temporal aspects into consideration for end-to-end learning for intelligent routing and traffic management.
- We proposed a novel Bayesian Neural Visual Odometry-based Localized Intelligent Routing, despite having a light architecture in comparison with OVEAP and RoadSegNet, is able to successfully perform smooth and robust traffic management for autonomous driving.
- The suitability of a new proposed Polynomial Regression-based Autonomous Vehicle Traffic Management algorithm is demonstrated by doing the performance evaluation of autonomous driving in simulated environment, where the BNVO-PR method shows the best performance in terms of routing time, routing overhead, routing accuracy and precision among four implemented solutions.

In the next section, the related work is presented. The Udacity Self Driving Car dataset used for data collection is described in section 3. Proposed method overall structure and implementation details of BNVO-PR are also given in this section. Results and discussion of the implementation of all three methods and inference during intelligent routing for traffic management are given in section 4. The conclusion is given in the last section.

2. RELATED WORKS

Over the recent years, Vehicular Ad-hoc Networks have gained high level of interest from both the scientists and engineers globally. This consideration is owing to the significance of VANET in addressing issues concerning traffic and safety and in enhancing entertainment facilities in Intelligent Transport Systems. An efficient data delivery method between vehicles called, an efficient Clustering Routing method employing clustering algorithm based on Density Peaks Clustering (DPC) and Particle Swarm Optimization (PSO) was presented in [9]. With this type of fusion method, average delay involved in clustering was reduced considerably.

New routing mechanisms are required for controlling immense traffic and ensure accurate routing. Conventional routing methods cannot satisfy the routing necessitates owing to the complicated traffic control situation. A method called, deep learning based intelligent routing strategy (DLBR strategy) that splits the network into numerous sub-blocks based on the recursive partition model was presented in

[10]. With this accuracy along with lower time complexity was ensured. In [11] numerous reinforcement learning techniques were applied for addressing intelligent communication between vehicles.

Over the recent few years, there has been exponential growth in Internet traffic due to the increasing numbers of associated mobile devices and evolutions in heterogeneous network. The immense evolution and increasing network traffic variability has put a proportional amount of stress on communication networks. An intelligent network traffic control method employing deep CNNs was presented in [12]. Performance analysis of deep learning method for significant data transmission was investigated in [13]. Differentiation between traffic types for intelligent routing was analyzed in [14]. Yet another intelligent control system was designed in [15] based on edge computing.

Managing failure and cost-aware traffic engineering are considered as two significant tasks performed in Network Operation Centers (NOC). Though based on implicit guiding principles, these network actions are said to be very difficult and cumbersome to be implemented however are also found to be difficult with explicit rules owing to high complexity. In [16], an Action Recommendation Engine (ARE) was designed with the purpose of learning implicit action rules with supervised machine learning. A holistic review on machine learning and artificial intelligence techniques for traffic management was investigated in [17]. A comprehensive survey of routing based 5G communication was designed in [18]. Yet another elaborate review on secured IoT-based smart system was presented in [19] using machine learning. A smart ML-based routing technique for VANETs to model traffic related messages in urban environments was proposed in [20]. Here, a novel ML-based forwarding algorithm was designed that in turn not only improved the packet delivery probability but also reduced average delay considerably.

As far as concerned, there is no proposal in the literature that includes a machine learning based intelligent routing for traffic management in wireless network concerning AVs. In the following sections, the proposal to design an intelligent routing and traffic management using novel machine learning is described.

3. Bayesian Neural Visual Odometry and Polynomial Regression-based Intelligent Routing For Robust Traffic Management

With the evolution of the Fifth Generation (5G) intelligent routing for traffic management in wireless network towards V2V communication is considered as the key technology to attain abstract level autonomous driving. Most of the prevailing autonomous driving systems depend on sensor equipment to monitor proximate environment. In case of the modern environment, the host AV is positioned with a camera in the center that in turn acquires sequential images while driving. In addition, the proximate vehicle (PV) or the AV closer to the host AV is at the fore of the host autonomous vehicle that in turn acquires the images by means of its own camera. Under the purview ofcommunication between AVs or simply V2V communication, intelligent routing ensures smooth and robust traffic management, therefore minimizing the overall congestion rate.

In this work, let us proceed with the assumption that PV communicates with the host AV by sending information, like, speed, steering angle, and images from central camera and so on, ensuring smooth and robust traffic management. With these data, V2V communication between AVs are said to be ensured. The AV here receives the information from the PV and combines the received information and start to process the two sets of data through a machine learning method called, Bayesian Neural Visual Odometry and Polynomial Regression (BNVO-PR). With the purpose of understanding the workings of AVs for traffic management in wireless networks, the four major constituents are perception, localization, prediction and finally, decision making.

The proposed method is based on the perception, nevertheless instead of directly utilizing the images captured by camera is taking into account. In addition, the archival movement state is considered as a paramount feature for making movement control decisions. As a result, a network architecture using a combination of Bayesian Neural Visual Odometry-based Localization and Polynomial Regression-based Autonomous Vehicle Prediction to entirely utilize both the spatial and temporal information for traffic management via intelligent routing is used. The elaborate description of the BNVO-PR based intelligent routing for traffic management in wireless networks in AVs is provided in the following sections.

3.1 Dataset description

In this work, the Udacity dataset is applied for conducting experiments. In the Udacity dataset an overall of 223GB of image frames are present with an average logs data from 70 minutes inclusion of annotation of latitude, longitude, gear, brake, throttle, steering angles, and finally, speed. Two separate days were used for data collections, with one day being sunny and the other day being overcast. The Frame Per Second (FPS) of each video data is found to be 20Hz with a resolution of 640*480 pixels, also the maximum speed of the AV and the proximate vehicle (PV) is set to be '$100km/h$'. The steering angle of the AV and the PV ranges between '$-\frac{\pi}{2}$' and '$\frac{\pi}{2}$', with '$\left[-\frac{\pi}{2}, 0\right]$' is designated as to go left, whereas '$\left[0, \frac{\pi}{2}\right]$' is designated as to go right. Moreover, the risk-tolerant of AV for steering angle is '4°' whereas the risk-tolerant for acceleration is '$4Km/h$' respectively.

3.2 Spatio-Temporal Motion Control-based Perception

One of the most significant characteristics that AVs must possess for traffic management is perception that assists the vehicles see the objects around it and identifying and classifying them accordingly (i.e., based on the data). For making accurate and timely decision, the AVs require to identify the objects around it instantaneously. As a result, in this work with the Udacity Self Driving Car dataset provided as input, the AVs necessitate classify precise point of interest according to five distinct classes (i.e., car, pedestrian, truck, biker and traffic light). Moreover, the expected distance between itself (i.e., AVs) and the proximate vehicles has also to be learnt for modeling routing in an intelligent fashion. Perception therefore enables in evaluating distance and determining to either apply brake or slow down and vice versa. To achieve accurate perception, distinct sensor for AVs is camera. In this paper, a Spatio-Temporal Motion Control-based Perception model is proposedto learn mapping between sample vehicle images 'SI' using both spatial and temporal information by PV interacting with AV via V2V communication for distinct classes 'C' respectively. Figure 1 shows the structure of Spatio-Temporal Motion Control-based Perception model.

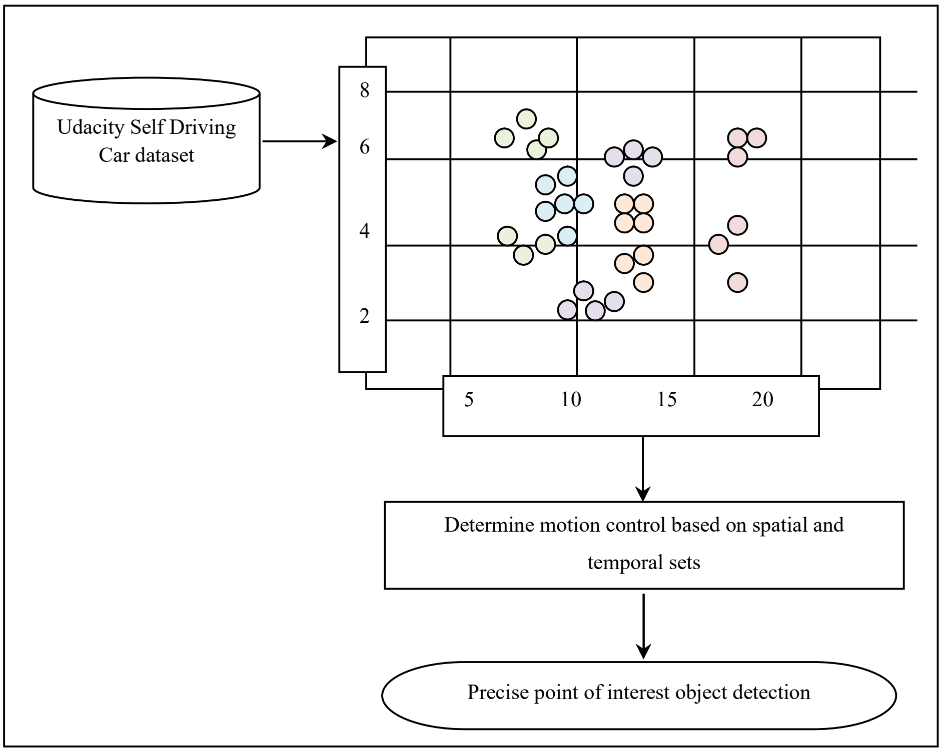

Figure 1 Structure of Spatio-Temporal Motion Control-based Perception model

As illustrated in the Figure 1, with the Udacity Self Driving Car dataset provided as input, first, input vector matrices are formulated for each sample vehicle images. Here, the input vector matrices are formulated according to the data obtained from the dataset as input. Following which, the motion control based on both spatial and temporal set values are determined with respect to distinct classes to determine point of interest object detection. As shown in the Figure 1, the sample vehicle images with respect to distinct classes forming the input vector matrix are formulated as equation(1).

$$IV = \{S_i C_j (X_{min}, Y_{min}), (X_{max}, Y_{max})\} \tag{1}$$

With the equation (1) input vector 'IV' formulation, PV on one hand collect data (i.e., spatial information) and assists the AV make motion control by sending data back to AV and on the other hand, the temporal information is provided by time-series images from both AVs and PV. The proposed method integrates both the spatial and temporal sets of data to regulate driving motion control for corresponding AV. Hence, the sample vehicle motion control is formulated as equation (2).

$$S(MC) = \{(X_{min}, Y_{min}), (X_{max}, Y_{max})\} \tag{2}$$

From the equation (2) results, the sample 'S' vehicle motion control 'MC' results is arrived at based on the positioning where the AVs sees the road and monitors the occurrence all around itself via extensive array of sensors. Based on the above description, according to our objective, the model is formulated as equation (3).

$$S(MC)_{AV}^{t+\Delta t} = \{S(MC)_{AV}^{t}, S(MC)_{PV}^{t}\} \tag{3}$$

From the equation (3), 'AV' stands for autonomous vehicle and 'PV' stands for proximate vehicle. The motion control of the AV at time 't' is determined based on the motion control of the AV at time '$S(MC)_{AV}^{t}$' and the motion control of the PV at time '$S(MC)_{PV}^{t}$' respectively. Each set of the motion control are described by four parameters that are the 'X_{min}', 'Y_{min}', 'X_{max}' and 'Y_{max}' respectively. The pseudo code representation of Spatio-Temporal Motion Control-based Perception is given in Algorithm 1.

Algorithm 1 Spatio-Temporal Motion Control-based Perception
Input: Dataset 'DS', Sample Vehicle Images '$SI = \{S_1, S_2, \ldots, S_n\}$',Actual Class '$C = \{C_1, C_2, \ldots, C_m\}$'
Output: Precise point of interest object detection results 'PoI'
1: **Initialize** '$m = 5$', 'n' 2: **Begin** 3: **For**each Dataset 'DS' with Sample Vehicle Images 'SI' and Class 'C' 4: Formulate input vector matrix as given in equation (1) 5: Formulate vehicle motion control as given in equation (2) 6: Formulate the objective function as given in equation (3) 7: **Return** object detected results 'PoI' 8: **End for** 9: **End**

As far as AVs are concerned, one important aspect to be addressed is routing accuracy. This is owing to the reason that all AVs data packets have to be sent and received in real-time and therefore, request response to sensor-based information and decision making requiresaccurate routing. As a result, higher routing accuracy rate remains the primitive performance metrics for AVs. As given in the above algorithm with the objective of improving the routing accuracy, in our work both the spatial and temporal information are gathered and subjected to motion control for returning the point of interest results, therefore acquiring accurate routing results (i.e., the minimum and maximum values of both x axis and y axis). By taking into consideration both the spatial and temporal information for processing accurate point of interest object detection results are obtained. In this manner, the routing accuracy is said to be improved considerably.

3.3 Bayesian Neural Visual Odometry-based Localized Intelligent Routing

Despite robust accurate point of interest object detection results obtained using Spatio-Temporal Motion Control-based Perception, however, the actual object in consideration has to be made (i.e., actual objects like car or truck or pedestrian has to be differentiated) so that any congestion can be avoided ensuring intelligent routing forsignificant traffic management towards smooth autonomous driving mode. This is arrived at only by means of Bayesian Neural Visual Odometry-based Localization model.

On one hand, Bayesian Neural Network assists in avoiding overfitting whereas localization is ensured via position and orientation of the vehicle obtained by means of Visual Odometry. Using Bayesian Neural Network optimal point estimation for the point of interest is obtained and localization in AVs measures the position and orientation of the vehicle by means of Visual Odometry. The process of VO is designed in such a manner by matching the key points in successive frames. With each frame, the position and orientation of each AV nearby with respect to the previous frame is measured that in turn aids in classifying the recognized objects as either car, truck, pedestrians and so on. Figure 2 shows the structure of Bayesian Neural Visual Odometry-based Localized Intelligent Routing model.

As illustrated in the Figure 2, with the Udacity Self Driving Car dataset provided as input, the objective remains in recognizing the object of interest with minimal routing overhead. With this object, a machine learning based Bayesian Neural Network is subjected to point of interest. Then, the position and orientation information are obtained using the Visual Odometry-based Localized Intelligent Routing model. Here intelligent routing refers to the identification of possible routes via Visual Odometry.

Let us consider the conventional neural network training we want to learn an input to output mapping (i.e., object or point of interest being an input and the type of object being an output '$q \sim f(p, W)$' via network 'f' with weights 'W' respectively. Moreover, the predicted class 'PoI' from the dataset 'DS' with object or point of interest detected '$PoI = (p_i, q_i)$' is designed with minimum loss '$Loss(DS, W)$' with respect to weights 'W'. This is mathematically stated as equation (4).

$$Loss(PoI, W) = \sum_{p_i, q_i \in DS} q_i - f(p_i, W) + \alpha \sum_k W_k^2 \quad (4)$$

From the equation (4), the loss of our method on point of interest 'PoI' from the dataset 'DS' '$Loss(PoI, W)$' is formulated based on the error between the target point of interest 'q_i' and output of network with input 'p_i' and weight 'W', in addition to the fine tuning parameter 'α' regularizing weight 'W' respectively. However, as we train on the predicted point of interest 'PoI' of training dataset 'PoI_{train}' but evaluate on the test dataset 'PoI_{test}' that in turn results in overfitting where network weights selected on training dataset though seems to work well on training dataset however do not perform well on testing dataset. To focus on this aspect, Bayesian Exact Inference function is employed to address on this overfitting is given in equation (5)

$$prob(W|PC) = \frac{prob(PoI|W)prob(W)}{prob(PoI)} = \frac{prob(PoI|W)prob(W)}{\int prob(PoI|W')prob(W')dW'} \quad (5)$$

From the equation (5), Bayesian Exact Inference function results are obtained for each target point of interest based both on the prior target point of interest '$prob(W)$' and the likelihood target point of interest '$prob(PoI|W)$' respectively. Despite the posterior point of interest distribution is easily formulated, however would results in huge routing overhead in case of obtaining integral for all probable values of 'W'.

As distinct weights and biases are represented for all the target point of interest it becomes very high dimension, therefore increasing the routing overhead involved in the overall localization process. In this work, by iteratively enhancing the approximation of weights and biases by means of Kullback Divergence Variational Inference optimized target point of interest is said to be arrived. This is mathematically formulated as equation (6).

$$PS = KLD[Prob(W||PoI)] = \int app_\varphi(W) \log \frac{app_\varphi(W)}{Prob(W||PoI)} \quad (6)$$

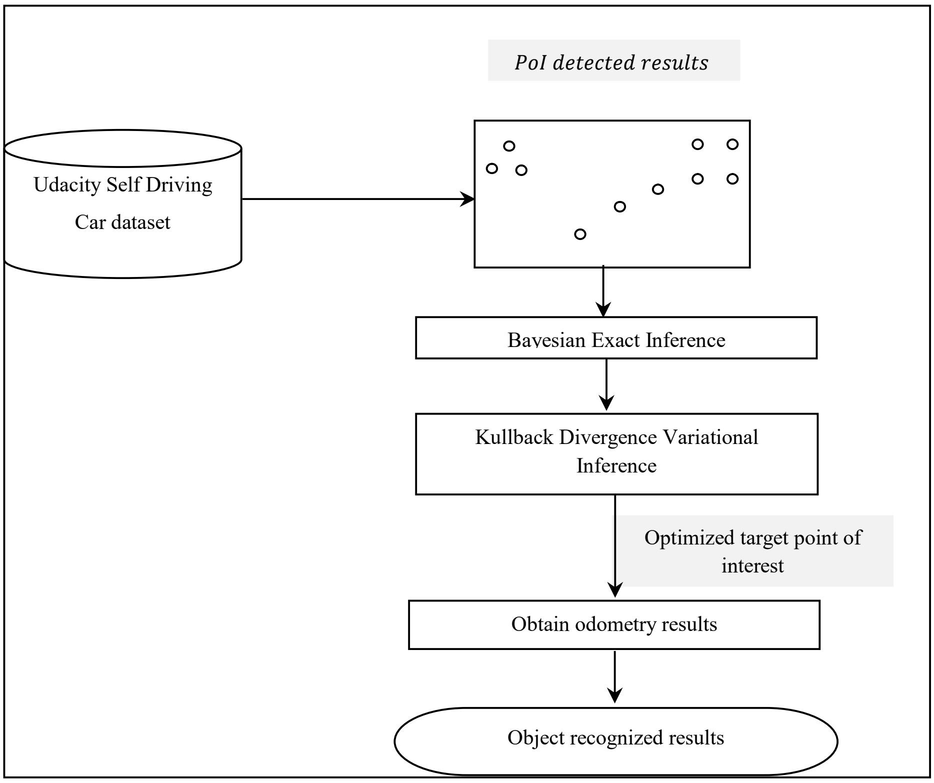

Figure 2 Structure of Bayesian Neural Visual Odometry-based Localized Intelligent Routing model

From the equation (6), the Kullback Divergence Variational Inference results 'KLD' are obtained based on the approximation 'app_{φ}' that in turn minimize the Kullback Divergence from approximate posterior target point of interest to the true posterior target point of interest. As a result optimality with minimal computation overhead is said to be ensured.

Following which the visual odometric calculation is performed for each resultant target point of interest to determine the position and orientation of AVs in action. In other words, after measuring the approximate posterior target point of interest to the true posterior target point of interest between two consecutive AVs, we need to transform it into real distance and heading angles and then add it to the previous position and orientation to update the current odometry information of the AV. First, the position of the current odometry information of the AV is as equations (7) and (8).

$$PoI\begin{pmatrix} p_{i+1} \\ q_{i+1} \end{pmatrix} = PoI\begin{pmatrix} p_i \\ q_i \end{pmatrix} + PoI\begin{bmatrix} \cos\left(\theta_i + \frac{\partial\theta_i}{2}\right) & -\sin\left(\theta_i + \frac{\partial\theta_i}{2}\right) \\ \sin\left(\theta_i + \frac{\partial\theta_i}{2}\right) & \cos\left(\theta_i + \frac{\partial\theta_i}{2}\right) \end{bmatrix}\begin{pmatrix} \Delta p \\ \Delta q \end{pmatrix} \quad (7)$$

$$PoI(\theta_{i+1}) = PoI(\theta_i) + PoI(\delta\theta_i) \quad (8)$$

From the equations (7) and (8), with the position '$PoI\begin{pmatrix} p_{i+1} \\ q_{i+1} \end{pmatrix}$' and orientation '$PoI(\theta_{i+1})$' information of the corresponding target point of interest of corresponding AV with respect to the previous target point of interest helps in classifying the actual objects accurately. The pseudo code representation of Bayesian Neural Visual Odometry-based Localized Intelligent Routing is given in Algorithm 2.

Algorithm 2 Bayesian Neural Visual Odometry-based Localized Intelligent Routing   **Input**: Dataset 'DS', Sample Vehicle Images '$SI = \{S_1, S_2, \ldots, S_n\}$', Actual Class '$C = \{C_1, C_2, \ldots, C_m\}$'
Output: Computationally-efficient object recognition 'OR'
1: **Initialize** '$m = 5$', 'n', point of interest results 'PoI'   2: **Begin**   3: **For**each Dataset 'DS' with Sample Vehicle Images 'SI', Class 'C' and point of interest results 'PoI'   4: Evaluate loss function while performing input output mapping as given in (4)   5: Formulate Bayesian Exact Inference function to address overfitting as given in (5)   6: Formulate Kullback Divergence Variational Inference optimized target point of interest as given in (6)   7: Evaluate the position of each object as given in (7)   8: Evaluate the orientation of each object as given in (8)   9: **Return**object recognized 'OR'   10: **End for**   11: **End**

As given in the algorithm 2, with the objective of reducing the routing overhead involved in the overall localization process, Bayesian Neural Visual Odometry model is applied. First, with the point of interest results provided as input, the objective remains in performing localization that in turn assist the AVs to know its initial position with minimal routing overhead. To achieve this objective first, Bayesian Neural regularization parameter is applied that with the aid of Kullback Divergence Variational Inference optimized target point of interest reduces the routing overhead. Following which the Visual Odometry-based Localization is performed by matching key points in consecutive frames that in turn assists in ensuring smooth and robust traffic management, therefore classifying roads, car, trucks and pedestrians in an efficient manner.

3.4 Polynomial Regression-based Autonomous Vehicle Traffic Management model

Finally, in this section, with the obtained point of interest results and object recognized results, to ensure smooth traffic management between AVs a mechanism to predict the actions of other AVs are said to be paramount. In this section, Polynomial Regression-based Autonomous Vehicle Traffic Management model is designed. With the AVs in action possessing a 360-degree view of its environment that in turn aids in acquiring all the information, once fed into the Polynomial Regression model can come up with all the probable moves that other AVs might make. This in turn can also aid in minimizing accidents considerably and therefore ensures robust traffic management.

We wish to fit a logistic function to the point of interest 'PoI' and object recognized results 'OR' (i.e., '$x_r = [PoI, OR]$') and the outcome of the traffic management results (i.e., '$y_r = (1,2,3,4)$'). The data points are indexed by the subscript 'r' that model from '$r = 50$' to '$r = 500$'. The 'x' variable here is referred to as the explanatory variable denoting the point of interest and objects being recognized whereas the 'y' variable denotes the categorical variable comprising of four categories '$I - quadrant$' or '$II - quadrant$' or '$III - quadrant$' or '$IV - quadrant$' respectively. Figure 3 shows the structure of Polynomial Regression-based Autonomous Vehicle Traffic Management model.

As shown in the Figure 3, with the Udacity Self Driving Car dataset, point of interest and object detected results provided as input, the objective remains in accurately managing the traffic, therefore ensuring road safety. With this objective, logistic function is first evolved. Following which, 360-degree view of its environment is modeled using the intercept and rate parameter, therefore ensuring accurate traffic management via four quadrants. The logistic function for the corresponding point of interest 'PoI' and object recognized results 'OR' is of the form as given in equation (9).

$$f(x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x)}} \quad (9)$$

From the equation (9), 'β_0' and 'β_1' represents the intercept and rate parameter of the corresponding samples 'x' in action respectively. Then for a given 'x_r' and 'y_r', let '$prob_r = prob\ (x_r)$', as already mentioned, AVs in action possessing a 360-degree view of its environment, optimum values possessing four quadrants (i.e., front view, rear view, left motion and right motion) have to be obtained. This is mathematically stated as in euqations (10) and (11).

$$\frac{\partial[Loss(PoI,W)]}{\partial\beta_0} = \sum_{r=1}^{R}(y_r - prob_r) \quad (10)$$

$$\frac{\partial[Loss(PoI,W)]}{\partial\beta_1} = \sum_{r=1}^{R}(y_r - prob_r)\, x_r \quad (11)$$

From the equation results (10) and (11) the AV prediction results are said to be obtained in an accurate and timely manner. Based on the probabilistic resultant values in '$prob_r$', the objects are said to be in the corresponding quadrants. By evaluating these functional results, continuous rendering of the surrounding environment are said to be made in a precise and accurate manner, therefore ensuring accurate prediction. The pseudo code representation of Polynomial Regression-based Autonomous Vehicle Traffic Management is given in Algorithm 3.

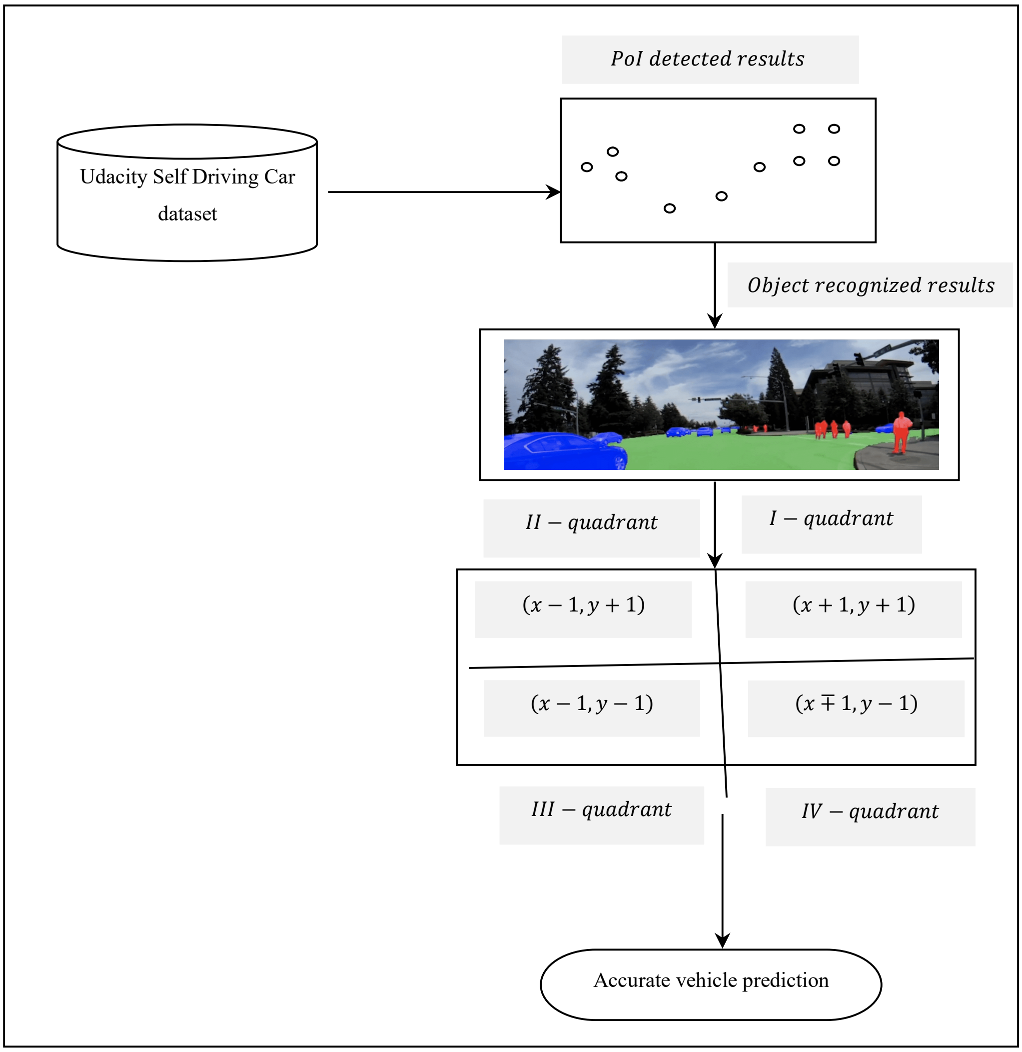

Figure 3 Structure of Polynomial Regression-based Autonomous Vehicle Traffic Management model

As given in the algorithm 3, with the objective of smooth and robust management of traffic in an accurate manner, logistic function for corresponding point of interest and object recognized results are initially formulated. Following which, derivatives of loss function are evolved in such a manner so as to interpret complicated visionary tasks and actuate kinematic maneuvers in AVs, therefore ensuring efficient traffic management. Finally, with the 360-degree view the logistic regression equation to measure the probability with respect to four quadrants and according to the positioning, traffic is managed in an accurate fashion.

Algorithm 3 Polynomial Regression-based Autonomous Vehicle Traffic Management

Input: Dataset 'DS', Sample Vehicle Images '$SI = \{S_1, S_2, \ldots, S_n\}$', Actual Class '$C = \{C_1, C_2, \ldots, C_m\}$'

Output: Accurate AV prediction

Initialize'$m = 5$', 'n'
Initialize object recognized 'OR'
Begin
For each Dataset 'DS' with Sample Vehicle Images 'SI', Class 'C', point of interest results 'PoI' and object recognized 'OR'
Formulate logistic function for the corresponding point of interest 'PoI' and object recognized results 'OR' as given in (9)
Evaluate the derivatives of loss function with respect to 'β_0' and 'β_1'
If '$prob_r$' lies between '0° and 90°'
Then objects present in the first quadrant
End if
If '$prob_r$' lies between '90° and 180°'
Then objects present in the second quadrant
End if
If '$prob_r$' lies between '180° and 360°'
Then objects present in the third quadrant
End if
If '$prob_r$' greater than '360°'
Then objects present in the fourth quadrant
End if
Return prediction results
End for
End

4 RESULTS AND DISCUSSION

The proposed Bayesian Neural Visual Odometry and Polynomial Regression (BNVO-PR) with vehicle to vehicle communication for safe autonomous driving was compared with Optimal Virtual Edge Autopilot Placement (OVEAP) [1] and RoadSegNet [2] that we re-implemented in order to conduct an objective performance evaluation of novel design. The methods of all three network architectures were implemented, trained with the same Udacity Self Driving Car Dataset and trained models were utilized for inference in simulator for autonomous driving. The results were compared in terms of performance metrics like, precision,routing overhead, routing time and routing accuracy. The experimental data processing is implemented via Python programming language.

4.1 Performance analysis of precision

In this section the performance analysis of precision is measured. The precision refers to the total number of correctly identified classes (i.e., car, truck, pedestrians) as a percentage of total number of pedestrians. The percentage of the number of correctly identified classes (i.e., car, truck, pedestrians) is given by the equation (12).

$$P = \frac{TP}{TP+FP} \tag{12}$$

From the equation (12), precision results 'P' are obtained based on the true positive 'TP' rate (i.e., the prediction result is correct when the sample is positive), false positive 'FP' rate (i.e., the prediction result is incorrect when the sample is positive), true negative 'TN' rate (i.e., the prediction result is correct when the sample is negative), and finally the false negative 'FN' rate (i.e., the prediction result is incorrect when the sample is negative) respectively. Table 1 lists the performance evaluation results of precision using the proposed BNVO-PR and existing methods, OVEAP [1] and RoadSegNet [2] by substituting the values in equation (12).

Table 1 Performance evaluation of precision using BNVO-PR, OVEAP [1], RoadSegNet [2]

Sample vehicle images	Precision		
	BNVO-PR	OVEAP	RoadSegNet
50	0.94	0.85	0.82
100	0.92	0.82	0.8
150	0.9	0.8	0.77
200	0.85	0.78	0.75
250	0.8	0.75	0.72
300	0.78	0.72	0.7
350	0.8	0.73	0.71
400	0.82	0.74	0.72
450	0.85	0.77	0.73
500	0.87	0.78	0.75

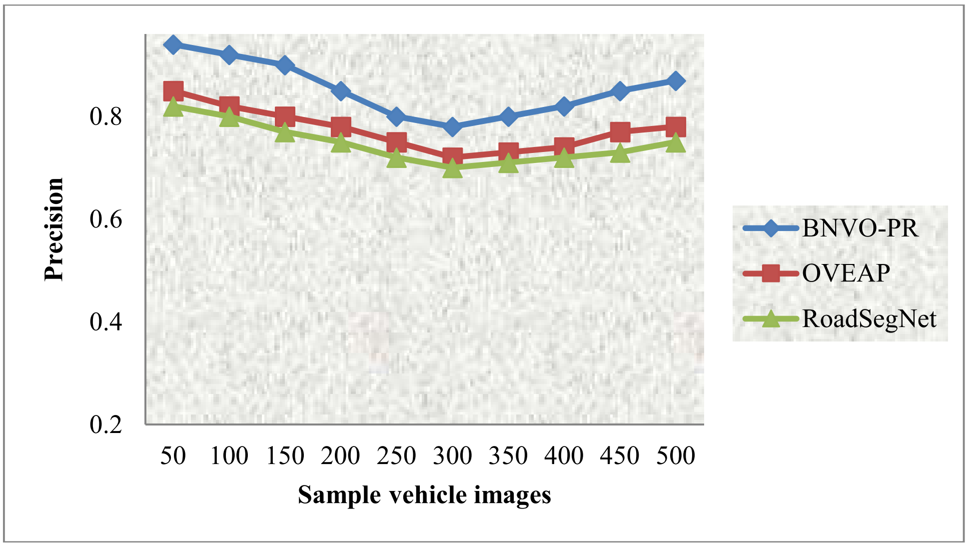

Figure 4 Precision versus sample vehicle images

Figure 4 illustrates the graphical representation of precision with respect to 500 sample vehicle images for simulation obtained at different time interval. As illustrated in the above figure, a decreasing trend was observed with sample vehicle images ranging between 50 and 300 whereas an increasing trend was observed greater than 300 sample vehicle images. However, precision rate was found to be better using BNVO-PR method upon comparison with [1] and [2]. For example, with 50 images involved in the simulation (i.e., 35 car images and 15 truck images), 33 car images were detected during the routing process when applied with BNVO-PR method, 30 and 29 car images were detected during routing when applied with [1] and [2]. As a result, improvement was found using BNVO-PR method. The reason behind the improvement was owing to the application of perception based on the spatial and temporal information for obtaining accurate point of interest. Here, the motion control according to both spatial and temporal information assisted in obtaining higher true positive rates, therefore ensuring intelligent routing. This in turn resulted in the improvement of overall precision rate using BNVO-PR method by 10% compared to [1] and 14% compared to [2].

4.2 Performance analysis of routing overhead

In this section the routing overhead involved in the localization process for ensuring smooth and secure data transmission is measured. While performing the localization process the position and orientation of vehicle have to be measured by matching the key points in successive frames. During this process a significant amount of overhead is said to be incurred and referred to as the routing overhead. This is measured as given in equation (13).

$$RO = \sum_{i=}^{n} SI_i * Mem\left[PoI\begin{pmatrix} p_{i+1} \\ q_{i+1} \end{pmatrix} + PoI(\theta_{i+1})\right] \quad (13)$$

From the equation (13), routing overhead 'RO' is measured based on the sample vehicle images involved in the simulation process 'SI_i' and the memory consumed in measuring the position and orientation information of target point of interest with respect to previous target point of interest. Table 2 lists the performance evaluation results of routing overhead using the proposed BNVO-PR and existing methods, OVEAP [1] and RoadSegNet [2] by substituting the values in equation (13).

Table 2 Performance evaluation of routing overhead using BNVO-PR, OVEAP [1], RoadSegNet [2]

Sample vehicle images	Routing overhead (KB)		
	BNVO-PR	OVEAP	RoadSegNet
50	1.5	2.35	3.05
100	1.85	3	4.15
150	2	3.55	5
200	2.35	4	6.35
250	2.85	4.85	7.25
300	3	5.25	8
350	3.55	6	9.55
400	4	7.35	12
450	4.85	9	14
500	6	11	15

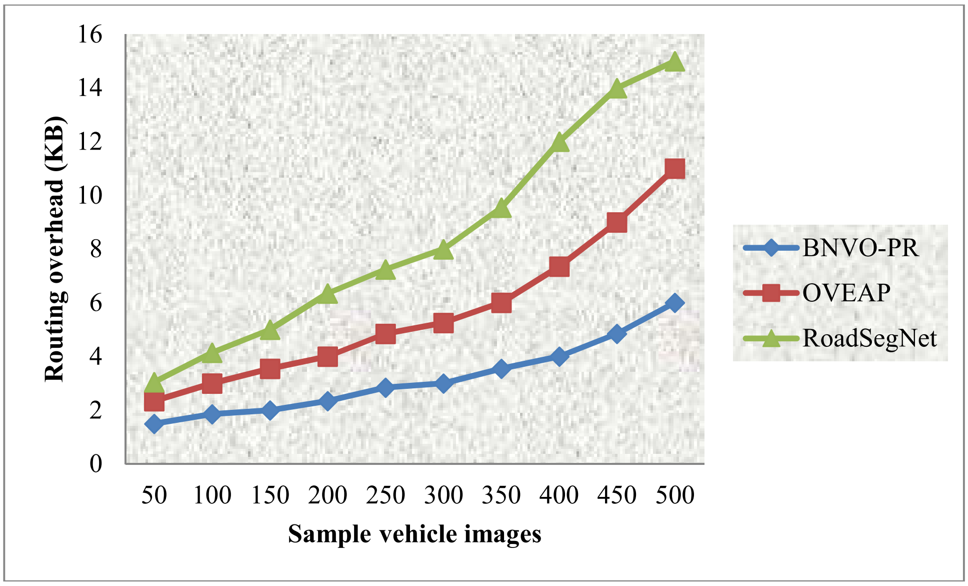

Figure 5 Routing overhead versus sample vehicle images

Figure 5 illustrates the graphical representation of routing overhead versus 500 distinct sample vehicle images. From the Figure 5 it is inferred that increasing the sample vehicle images results in the increase in number of point of interests to be located for intelligent routing. This in turn would increase the routing overhead for localization and therefore traffic management also. However, simulations performed with 50 sample vehicle images using the proposed BNVO-PR method was observed to be 1.5KB, 2.35KB using [1] and 3.05KB [2]. The reason behind the minimum routing overhead incurred using BNVO-PR method was owing to the application of Bayesian Neural Visual Odometry-based Localized Intelligent Routing algorithm. By applying this algorithm, two distinct factors were taken into consideration, i.e., the position and orientation of each AV nearby with respect to the previous frame using Visual Odometry and addressing overfitting issues arising during localized intelligent routing by means of Bayesian Neural Network. By combing these two functions, approximation of weights and biases were ensured by means of Kullback Divergence Variational Inference optimized target point of interest, therefore guaranteeing intelligent routing for traffic management. This in turn reduced the routing overhead using BNVO-PR method by 42% compared to [1] and 61% compared to [2] respectively.

4.3 Performance analysis of routing time

In this section the routing time for V2V communication is presented. Routing time for V2V communication refers to the time involved in the transmission of data for autonomous driving. Earlier and better the routing time, more efficient the precision is also said to be. Routing time for V2V communication is measured as given in equation (14).

$$RT = \sum_{i=1}^{n} SI_i * Time\ (DT) \quad (14)$$

From the equation (14), the routing time 'RT' for significant V2V communication is measured based on the sample vehicle images involved in the simulation process 'SI_i' and the actual time consumed '$Time\ (DT)$' in transmitting the measured data (i.e., the maximum and minimum position values of x axis and y axis). It is measured in terms of milliseconds (ms). Table 3 lists the performance evaluation results of routing time using the proposed BNVO-PR and existing methods, OVEAP [1] and RoadSegNet [2] by substituting the values in equation (14).

Table 3 Performance evaluation of routing time using BNVO-PR, OVEAP [1], RoadSegNet [2]

Sample vehicle images	Routing time (ms)		
	BNVO-PR	OVEAP	RoadSegNet
50	1.25	1.6	2.25
100	1.85	2.35	3
150	2	2.85	3.85
200	2.35	3.15	4
250	2.85	4	4.85
300	3	4.35	5.25
350	3.85	5	6.35
400	4.35	5.85	7.85
450	4.85	6.25	8
500	5.25	7	9.35

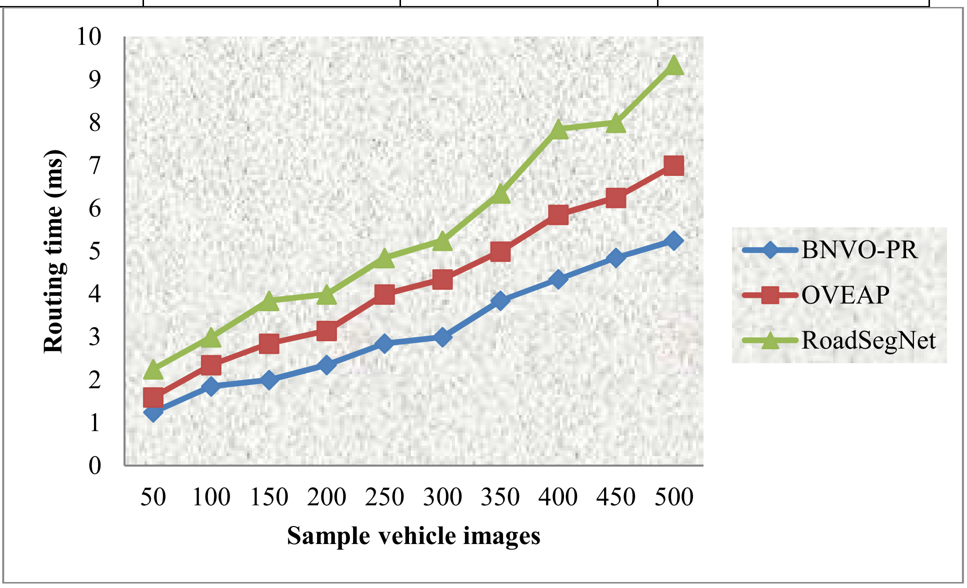

Figure 6 Routing time versus sample vehicle images

Figure 6 shows the routing time or the time involved in intelligent routing for traffic management with respect to distinct numbers of AVs in process. From the Figure 6 it is inferred that increasing the sample vehicle images results in the increase of point of interest and therefore increasing the overall localization process also. However with simulations performed for 50 sample vehicle images, the time for intelligent routing, i.e., the time consumed in performing the overall localization process was found to be 1.25ms using BNVO-PR method, 1.6ms using [1] and 2.25ms using [2]. From this result it is inferred that the intelligent routing time using BNVO-PR method was found to be comparatively lesser upon comparison with [1] and [2]. The reason behind the minimization of routing time using BNVO-PR method was owing to the application of Bayesian Neural Visual Odometry-based Localized Intelligent Routing algorithm. By applying this algorithm, initially with the point of interest results provided as input, localized intelligent routing is performed that in turn assist the AVs to know its initial position with minimal routing time via Bayesian Neural regularization parameter with the aid of Kullback Divergence Variational Inference optimized target point. Following which the Visual Odometry-based Localized Intelligent Routing is performed by matching key points in consecutive frames that in turn assists in ensuring intelligent routing by classifying roads, car, trucks and pedestrians in an efficient manner. With this the intelligent routing time using BNVO-PR method was said to be reduced by 25% compared to [1] and 42% compared to [2].

4.4 Performance analysis of routing accuracy

Finally, in this section the routing accuracy for autonomous driving is evaluated. Routing accuracy refers to the accuracy rate at which the routing is ensured. This routing accuracy is measured as given as Equation (15)

$$RA = \sum_{i=1}^{n} \frac{SI_{RA}}{SI_i} * 100 \quad (15)$$

From the equation (15), routing accuracy 'RA' is measure based on the sample vehicle images 'SI_i' involved in the simulation process and the sample vehicle images routed accurately 'SI_{RA}' for further processing. It is measured in terms of percentage (%). Finally, table 4 lists the performance evaluation results of routing accuracy using the proposed BNVO-PR and existing methods, OVEAP [1] and RoadSegNet [2] by substituting the values in equation (12).

Table 3 Performance evaluation of routing accuracy using BNVO-PR, OVEAP [1], RoadSegNet [2]

Sample vehicle images	Routing accuracy (%)		
	BNVO-PR	OVEAP	RoadSegNet
50	92	88	86
100	93.55	90.15	87.15
150	89.15	88	86
200	85.35	83	80
250	83	80	75
300	82.55	75	72
350	84	77	73
400	86.15	78	74
450	88	79	75
500	90	81	77

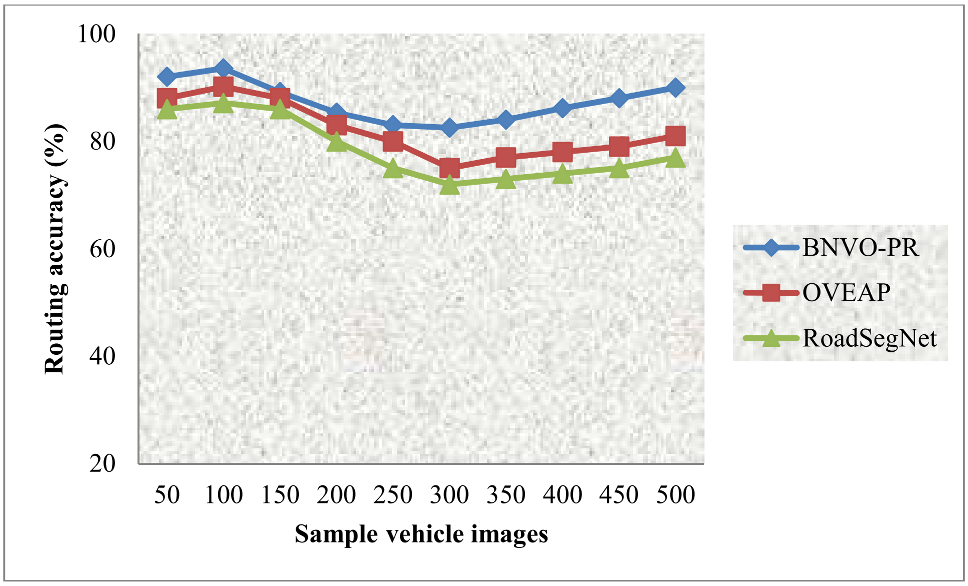

Figure 7 Routing accuracies versus distinct sample vehicle image

Finally, Figure 7 shows the routing accuracy involved in the process of traffic management in wireless networks. From the figure 7, the routing accuracy is neither said to be increasing or decreasing with the increase in the sample vehicle images. This is because five different classes of sample vehicle images are involved in the simulation process and also positioned arbitrarily. For example with simulations performed using 50 sample vehicle images, 46 sample vehicle images were correctly identified as it is and therefore ensuring intelligent routing for traffic management using BNVO-PR method 92%, 88% using [1] and 86% using [2] respectively. The reason behind the improvement was owing to the application of Polynomial Regression-based Autonomous Vehicle Traffic Management algorithm. By applying this algorithm, logistic function for point of interest and object recognized results were initially obtained. Following which, derivatives of loss function were evolved in such a manner so as to interpret complicated visionary tasks ensuring smooth traffic management. Finally, employing 360-degree view the logistic regression equation to measure probability with respect to four quadrants according to the positioning, the routing accuracy was said to be improved using BNVO-PR method by 7% compared to [1] and 12% compared to [2]. This in turn would pave the mechanism for smooth and robust traffic management in wireless networks for AVs in concern.

5 CONCLUSION

The evolution of machine learning based intelligent routing for traffic management in wireless network leads to great advancement in novel approaches to known problems. However, the AVs application often requires machine learning solutions which can be achieved by careful design of neural network model architecture. The Bayesian Neural Visual Odometry presented in this paper is one possible solution for intelligent routing for smooth and robust traffic management in autonomous driving. The aim of this work is to achieve successful autonomous driving using a Bayesian Neural Visual Odometry that is suitable for inference and deployment in wireless networks. Having this in mind, we designed and implemented Bayesian Neural Visual Odometry and Polynomial Regression (BNVO-PR) with vehicle to vehicle communication for traffic management ensuring intelligent routing for autonomous driving. The main contribution of proposed method is the novel solution that is computationally efficient due to application of separate mechanism for intelligent routing and traffic management accordingly. The complexity of Bayesian Neural Visual Odometry-based Localized Intelligent Routing and Polynomial Regression-based Autonomous Vehicle Traffic Management algorithm is determined by the number of operations in one iteration, and our BNVO-PR method has shown similar qualitative results gained with much fewer operations in comparison with other state-of-the-art methods explored in this paper.

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