

An Optimized Uncertainty Aware Sensor Fusion approach for Autonomous Vehicles using Bayesian Neural Networks

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Abstract: Autonomous vehicle is a one of the most emerging technologies that have started being used in developed countries for public transportation, such as robotaxis, autonomous buses. During uncertain situations, such as heavy rain, mist and bad weather the reliability of the sensor values may compromise due to decreased visibility, increased sensor noise, and inconsistencies in sensor reading. In this paper, uncertainty aware sensor fusion approach is proposed based on Bayesian Neural Networks (BNN) to address this problem. Uncertainty estimation and redundancy graph construction provides the stability to analyze the sensor data readings. It also enhances the accuracy and robustness in state estimation. An adaptive confidence weight helps the system to prioritize the sensors and the graph structure ensures the propagation of probabilistic data's across the nodes. The simulation result demonstrates the improved robustness and reliability in the multi sensor fusion process and better accuracy in the state prediction and decision making process.

Keywords: Autonomous vehicles; Uncertainty aware Sensor fusion; Bayesian Neural Networks

Introduction

The autonomous vehicles are playing major role in modern technology innovations. Nowadays in many countries like USA, China, automated vehicles are used as a public transport within the trained places. It involves edge artificial intelligence that brings the decision making and processing capabilities from the cloud to the edge devices. Various levels of vehicles are available starting from level 0 to level 5. Level 0 cars has no autonomous features, that is operated manually. Level 1 vehicle is operated by the driver with limited autonomous features. Level 2 vehicles require driver but no need to monitor the environment and he must be ready to take a control at any time. In Level 3 and 4 vehicles there is no need of driver; the vehicle can perform all operations under certain conditions. Level 5 vehicles don't need the driver and complete operations are autonomous. All these categories involves a process of sensor fusion, deployment of machine learning and deep learning models, decision making, route estimation in Geofencing and finally acceleration of actuators. During operations first phase, sensors like LiDAR, Radar, Ultrasonic sensor, High Definition cameras, Global Positioning systems collect the data and sensor fusion taken place. Based on the output from sensors, machine learning and deep learning models are applied for the prediction, which leads to the decision making on the state of the vehicles. Next path finding process is employed for planning the path to travel. In this, various path finding algorithms like dijkstra's algorithm, and some metaheuristic algorithms are used. The vehicles can be travelled in the Geofencing area in which the vehicle was already trained. As the autonomous vehicles are available for the public transport, during some uncertainty conditions like heavy weather, fog and mist it is unsure that the sensors will acquire the real data from the environment resulting in imperfect output from sensor fusion. It may lead the vehicle to handover the control to human during this

situation. To address this uncertainty issue in this domain we propose a new approach which will improve the robustness of the sensor fusion results.

Related Work

In [1], a new algorithm is proposed, based on inertial odometry of LiDAR especially for urban environments. It implements distribution to distribution approach instead of using the point to point approach. With the help of Gaussian distribution, covariance is measured. It also considers Z axis drift using ground plane. This approach manages the uncertainty. In [2], the authors discussed about the survey of sensor fusion approaches and its transformer representations, sensor fusion based on transformer with respect to camera radar and camera LiDAR and a complete review of state of the art methods for identifying the research gap. In [3], the impact of high performance virtual sensors on the vehicle is analyzed. Integration of vehicle motion models and machine learning models creates any impact on measuring vehicle sideslip angle directly from sensor onboard information.

In [4] a new deep neural network algorithms based on probabilistic approach is presented, it integrates RGB camera values and LiDAR point clouds and gives better 3D view in object identification. In this uncertainties are modeled for regression and classification tasks. And using sampling approach uncertainties are leveraged to provide training for fusion network. In [5] various types and levels of autonomous vehicles are given and its characteristics are analyzed, like up to what level human supervision needed and what are the levels are fully autonomous. Some of the processes under perception phase such as sensor refinement object refinement, situation refinement and decision making are also reviewed. In [6] a new framework MMLF is proposed at decision level of the autonomous vehicles. Uncertainty quantification approach with evidence theoretic has been incorporated which is Dempster Shafer theory based. Through that a better confidence measurement is given and it's mathematically grounded.

In [7] some of the challenges in reliability assessment and misclassification in capacitor detection is discussed. In this Bayesian deep-learning approach is discussed, this is based on the integration of multiple domain signal enrichment with respect to time and frequency. In [8] some of the challenges in semantic segmentation and multimodal object detection in autonomous cars are discussed. On test vehicles impact of onboard sensor, open datasets are analyzed. Object detection background information is monitored and different types of fusion approaches and its challenges are also given. In [9] the method for improving accuracy of the detection process during working for real time operations. Reliability in bbox(bounding boxes) of uncertainty localization is predicted in this approach. After predicted localization uncertainty some schemes are introduced such as Gaussian YOLOv3. Through which false positive gets minimized and true positive gets maximized so the accuracy is improved.

In [10] a two localization algorithms are proposed to manage the biases, goal and state of the bias are measured parallel in the first approach, bias compensation based on prior is utilized in the next approach. A new optimization algorithm is analyzed which is designed for feasible platform trajectory prediction and terrain uncertainty, bias uncertainty are taken for consideration. In [11] a novel framework is given which helps to predict the uncertainty in the domain of complex fusion networks in that sporadically signals are available. In this approach artificial neural network generates a surrogated

model of the uncertainty of the sensor from the data directly assuming no idea about sensor characteristics.

Proposed work

In this research work a new approach is proposed for sensor fusion in autonomous vehicles, which will help the vehicle to improve robustness during uncertainty conditions such as bad weather, heavy rain, fog & mist. Existing approach achieves the better results during normal conditions, by considering the deterministic features. But during these unexpected situations the control will be handed over to the human or the operations will be hold for some time until the uncertainty condition ends. To overcome this unexpected situation, the Bayesian Neural Network (BNN) algorithm is taken in to consideration for sensor fusion in the place of Convolution Neural Network. In this approach Probabilistic features are extracted instead of extracting the deterministic features. They are lane, edges and objects. To ensure the model accuracy in these uncertainty conditions the modules like uncertainty Prediction, redundancy based data modeling and weather sensitive confidence assessment are incorporated. Figure 1 represents the proposed BNN based uncertainty aware sensor fusion framework.

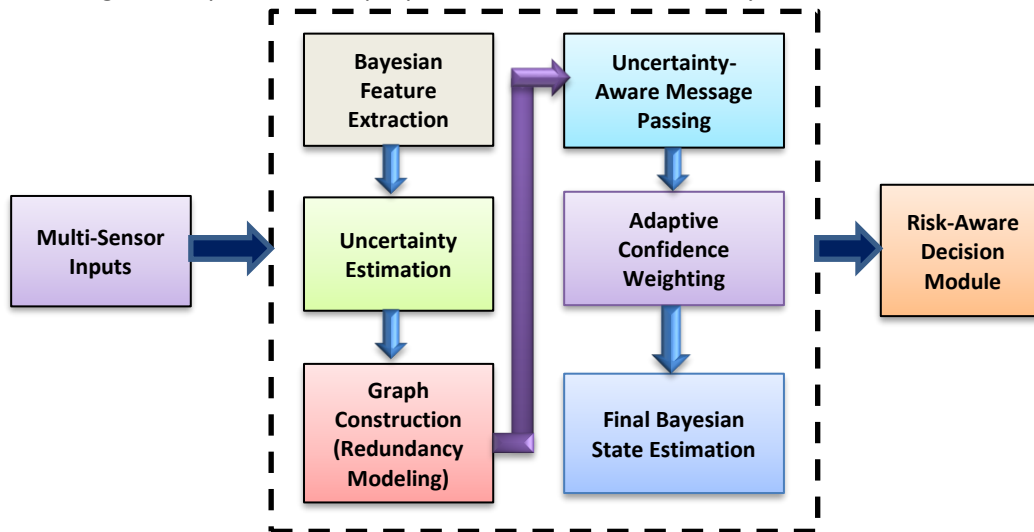


Figure 1. Proposed BNN Based sensor fusion approach

The autonomous vehicle uses multiple sensors like Radar, LiDAR, Ultrasonic sensors, High Definition (HD) cameras etc. All sensors capture the real-world data in various formats like LiDAR represents the data in the form of x,y,z spatial coordinates and intensity 3D point cloud data. This is used to measure the distance using the laser beam. The radar generates object detection list and range doppler data to detect the object distances and speed. The ultrasonic sensors produce the distance measurements in centimeters or meters, High definition camera captures the visual information by generating the video streams and digital image frames. Data from sensor undergo cleaning process, where data normalization, calibration, noise removal processes are done. Synchronization of sensor timestamps is made to ensure that the data's from the different sensors are aligned and accurate. The existing sensor fusion system works on the deterministic predictions, independent sensor noise and fixed confidence weighting. This may lead to unsafe and affects the reliability of decision making during some uncertainty conditions. Probabilistic based graphical fusion approach is proposed in which the

redundancy of the sensor is quantified, uncertainty is modeled explicitly, and sensor confidence is adjusted dynamically so the reliability gets propagated. Let B_x be a true state of environment, U_x^a be an observation of the sensor from modality 'a', we can estimate $E(B_x | U_x^1, U_x^2, U_x^3, Y_x)$, the

$$\text{Bayesian factorization can be represented as } E(B|U) \propto E(U|B) E(B) \quad -- (1)$$

Bayesian uncertainty modeling

Bayesian uncertainty modeling is applied to improve robustness during these uncertain conditions. Based on the Bayesian uncertainty modeling each sensor can be modeled as $X_i = f_i(y; \theta_i) + \epsilon_i$ -- (2)

Here, ϵ_i - aleatoric noise and, θ_i -posterior distribution

$$\text{Vibrational inferences can be } p(\theta_i) = \gamma(\mu_i, \rho_i^2) \quad -- (3)$$

$$\text{Predictive mean can be } \mu_i = E[f_i(y)] \quad -- (4)$$

$$\text{Predictive variance can be } \rho_i^2 = \text{Var}[f_i(y)] + \rho_{aleatoric}^2 \quad -- (5)$$

In this Bayesian uncertainty modeling the system checks how uncertain each prediction and feature are. Different types of uncertainty quantities like aleatoric uncertainty that is based on sensor noise and weather conditions. Epistemic uncertainty due to the lack of training data, novel scenarios, and model uncertainty due to confidence gap in the neural networks is validated. After adopting the proposed model, each feature will have a variance, covariance and mean estimate that give a clear idea about how much each signal to be treated.

Graph-Based Redundancy Modeling

Sensor fusion takes place from data produced from the different sources. Timestamp is assigned to each frame of the signal, these timestamp plays a major role in the sensor fusion process, and because it is not sure that the each sensor output is synchronized with in the captured time slots. The graph based redundancy modeling allows the system to build the graph where edges are relationship between the nodes and sensor objects. The generated graph will encode physical consistency, cross sensor agreement and temporal or spatial relationships. Let nodes be a sensors and edge weights are redundancy strength the graph can be represented as $G = (V, E)$.

$$\text{Redundancy through mutual data's } K_{xy} = L(M_x, M_y) \quad -- (6)$$

$$\text{The standardized credibility score } K_x = \sum_{x \neq y} \frac{L(M_x; Z)}{L(M_x, M_y)} \quad -- (7)$$

From the proposed model it is clear about which contradicts each other, which signal support each other, where the redundancy exists. The extracted features and sensor data's are given as a graph structure. Two nodes of the connected graph are made by the pedestrian identified by LiDAR and camera. This will improve the robustness of the system. Even if any sensor gets failed, perfect prediction is resulted.

Uncertainty Aware communication:

In this phase, the Probabilistic communication is started between the nodes of the constructed sensor graph instead of deterministic message passing. Let h_p^{new} – be the updated findings of the node 'p', h_q – finding of the nearby node 'q', w_{pq} – weight represents the reliability of a message from node 'q', $Message(h_q)$ be the node 'j's probabilistic information. With respect to above values, every node in the graph informs its findings (Estimated probability) by aggregating information's from its nearby nodes:

$$h_p^{new} = \sum_q w_{pq} Message(h_q)$$

Propagation of information across multiple sensors during uncertainty is taken. For example, if a camera gets blurred but the radar confidently identified the pedestrian, the higher influence will be given to the radar signals. The confidence of identified object gets increased when both radar and camera agrees. If both sensors disagree and uncertain, ambiguity arises and seeking for additional observations.

Experimentation and Results

The Proposed framework has been implemented with the help of MATLABR2025 simulation. In autonomous vehicles, multi sensor perception is taken for consideration. In this aspect multiple heterogeneous sensors provide the observations for the same environment. In this framework, it is analyzed that how BNN based redundancy modeling and adaptive confidence weighting helps the sensor fusion approach and improves the robustness during uncertainty conditions like heavy weather, fog etc. For Bayesian uncertainty computation and state estimation, Matrix operation is used. Graph function is used to build a redundancy graph of sensor. For visualization of fusion results and sensor data plotting functions are used. For estimation probabilistic uncertainty statistical modeling is used. Table 1 gives the simulation setup details with the values taken and parameters. Table 2 represents the different types of sensor's uncertainty values and the corresponding adaptive confidence weight given to sensors with respect to those uncertainties.

Table 1. Simulation setup

| Parameter | Details |
|---------------|--|
| Total Sensors | 5 |
| Sensors | HD Camera, LiDAR, Radar, GPS, Ultrasonic sensors |
| State | 2D |
| Fusion Type | Bayesian sensor fusion |

Table 2. Uncertainty Levels of sensor

| Sensor | Uncertainty Value | Confidence weight |
|--------|-------------------|-------------------|
| S1 | 1.64 | 0.21 |
| S2 | 1.13 | 0.24 |
| S3 | 1.48 | 0.20 |
| S4 | 1.67 | 0.22 |
| S5 | 1.52 | 0.14 |

In table 2 greater values represents the higher uncertainty and minimum values indicates the lowest uncertainty. Sensor with minimum uncertainty gets better confidence weights. To observe the connections among the sensor findings the graph is build where each sensor is considered as nodes. The association between the sensor measurements is taken as edges. Uncertainty aware message passing is enabled among the sensors by this graph.

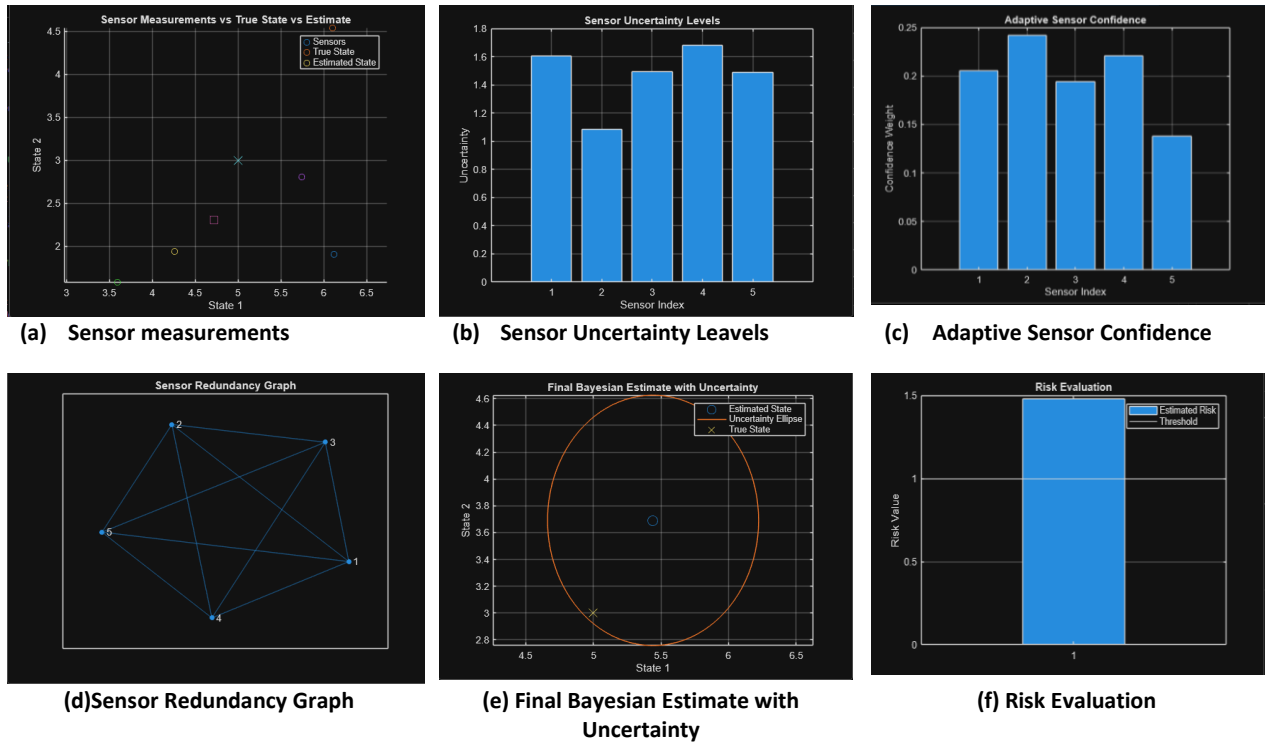


Figure 2. Simulation outputs in the form of Graph

Simulation results in the form of graph are represented in figure 2. Sensor measurements between state1 and state2 represented in figure 2(a). Sensor uncertainty levels are given in the figure 2(b) and 2(c) estimates the adaptive confidence weight. The generated sensor redundancy graph is given in the figure 2(d). Bayesian uncertainty estimation 2(e) represents the final state estimate by blue circle, yellow cross gives the true state and the uncertainty region is marked as ellipse. Finally the risk evaluation is represented in 2(f). From this research work, it is found that measurement errors and sensor noise are reduced after adopting the Bayesian based sensor fusion during uncertain condition.

Table 3. Results of final state estimation

| | True state | Estimated State |
|----------|------------|-----------------|
| State -1 | 5.03 | 5.44 |
| State-2 | 3.02 | 3.72 |

From table 3, it is clear that a final state estimation value of the proposed framework improves accuracy and robustness by 12%. The uncertainty ellipse clearly denotes the probabilistic region of confidence on the estimated state.

Conclusion

The results clearly confirm that the efficiency of the proposed Uncertainty Aware Bayesian Neural Networks based Sensor Fusion approach for Autonomous Vehicles is improved. Combining uncertainty measurement and graph based redundancy modeling; adaptive confidence weighting remarkably increases the robustness on estimation of state during some uncertainty conditions like heavy weather or fog etc. Adopting the probabilistic based feature extraction approach helps to achieve improved accuracy in computing the uncertainty. The uncertainty estimation helps to measure the

reliability of each signal. The redundancy based graph construction performs the sensor fusion very effectively and permits the system to utilize correlations among the sensor signals. So the proposed framework fine-tunes the sensor signals dynamically with respect to their credibility. This characteristic is very important during the uncertainty conditions when some sensors efficiency reduced. The overall result shows the proposed BNN based optimized uncertainty aware sensor fusion framework enhances the reliability of the multi sensor perception in autonomous vehicles, making it adoptable in real time intelligence transportation domain.

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