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A Review on Techniques to Enhance the Accuracy and Efficiency of Target Detection

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Abstract: Object detection plays a pivotal role in computer vision applications, with many methodologies constantly being developed to improve accuracy and efficiency. This paper presents an innovative approach that aims to enhance the accuracy of object detection through the use of more advanced and accurate methods. The proposed method leverages state-of-the-art techniques, including deep learning architectures, feature engineering, and optimization filter algorithms, to achieve superior results compared to existing methodologies. The study evaluates the performance of the proposed method using benchmark datasets and demonstrates its effectiveness in accurate object detection via the use of the Bayesian filter algorithm. The findings of this review highlight the potential impact of adopting more accurate object detection methods on advancing the capabilities of computer vision systems, paving the way for researchers in the field to improve applications in areas such as autonomous vehicles, surveillance, and robotics.

Keywords: Object Detection, Deep Learning Architectures, Bayesian Filter Algorithm, Computer Vision Systems, Autonomous Vehicles, Surveillance, Robotics, Sliding Mode Controller (SMC).

1. Introduction

In the dynamic field of computer vision, the search for more accurate and reliable object detection methodologies has stimulated continuous innovation. As we navigate an era of unprecedented technological advancement, integrating cutting-edge technologies has become essential to meet the increasing demands of real-world applications. This paper delves into the frontiers of object detection, presenting a new and improved approach that incorporates the power of virtual filtering to enhance accuracy and robustness. Object detection is the backbone of countless applications, from autonomous navigation and surveillance to augmented reality. Traditional methods, while laudable, often face challenges posed by complex scenes, occlusions, and variable lighting conditions. The integration of virtual filtering, a probabilistic framework famous for its ability to model uncertainty and iteratively improve predictions, provides a promising way to address these challenges and raise the accuracy of object detection. In this paper, we provide a comprehensive exploration of our proposed method, illustrating the basic principles underlying the combination of advanced object detection techniques with virtual filtering [1-3]. The integration of these methodologies aims not only to detect objects with high accuracy, but also to provide the system with the ability to adapt and improve predictions in dynamically changing environments. Through experimental evaluations on benchmark datasets, we demonstrate the effectiveness of our approach compared to traditional methods, and demonstrate the impact of default filtering on object detection accuracy. Through this scientific review, the complexities of the proposed technologies will be revealed, highlighting their theoretical foundations, implementation details, and practical implications. This endeavor contributes to the ongoing discourse on object detection methodologies and provides a nuanced perspective on the integration of virtual filtering as a catalyst for enhancing accuracy and adaptability in computer vision applications. This endeavor contributes to expanding knowledge of the evolving landscape of object tracking methodologies, providing insight into the potential of using cutting-edge technologies in conjunction with sensors for real-time and real-time tracking applications. Figure 1 shows a schematic diagram of object tracking technologies such as mobile cars [2-5].

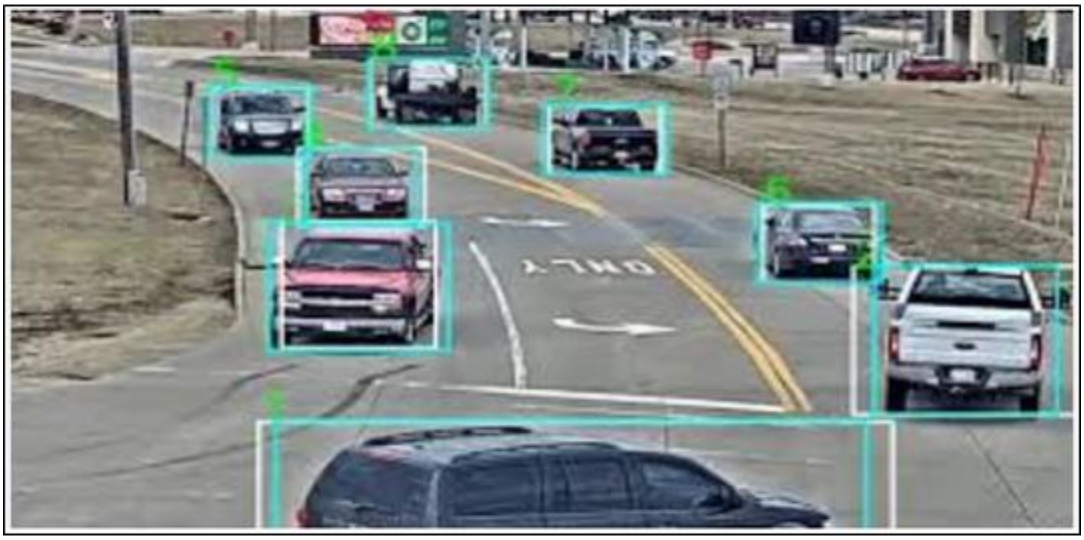

Figure 1 : A schematic diagram of object tracking technologies such as mobile cars [2-5].

Movig object analysis, are considered as real-time detection of moving objects is an important implemetation. Moving object detection is utilized to locate variations in pictures and whether there is either alternations, next extracts the animated object. The moving object is detected by separating the foreground object, that is, the moving object, along the stationary data recognized as background [6-8]. Subtraction in the background is the essential step employed in detecting moving objects to detect people, vehicles, etc. Through video processing, the primery video is converted towards picture frames [9, 10]. Pretreatment is an initial step which should be achieved for removal noise in the images. The picture will further be improved by pretreatment strategies. Feature extraction is an approach for capturing the visual content of pictures for indexing and retrieval. Feature extraction is a kind of dimensionality reduction strategy. Transforming the input data to form a group of features is named extraction feature. The chosen feature should include sufficient data aroud the picture with no other specific knowledge is required for them extraction [11]. The chosen feature should be simply to evaluate the selected features. The features might be of either kind like color, shape, etc. There is a various feature extraction techniques. Principal component analysis, Gabor filter, String code Character Contour histogram, GLCM, etc. are several of the feature extraction strategies. Extracted features are categorized as required. There is various classification approachs [12]. Among such artificial neural networks a classifier which might be trained depending on demands. These might be neurons trained correspondig to inputs and might be simply modified as per criteria selected for classification. Over recent years, areas such as image analytics with visual analytics have gained a wide range of uses. Spectral analysis with artificial intelligence are two major innovations that stand out in specialized scientific forums. There are recent attempts to represent and simulate the visual vision of humans, where the personal vision is the natural, tangible and comprehensible sense of the human being, with the emergence of an impression of the three-dimensional external world [13,14]. Human intelligence has been prepared over the years to recognize and process scenes captured by the eyes. These instincts are at the core of most new innovations. Recent research is now encouraging scientists to uncover more subtleties in the formation and knowledge of images. Such advancements are due to best-in-class technologies such as CNN technology [15]. Applications from Google, Facebook, Microsoft and Snapchat in general are among the implications of the massive improvement in computer rendering and applications of deep learning techniques. Through the time lapse, vision-based innovation has changed from a detection-only methodology to a wise processing frameworks that may get this current reality. PC vision applications type moving path, monitoring and independent moving object trajectory for object recognition and follow-up as major difficulties. For vehicles with other real objects, video reconnaissance is a unique climate. In some studies, effective computation is a dedicated application of body location and follow-up video surveillance in a complex climate [16-18]. The application field of object location and tracking focuses inseparably from computer vision applications. Where shape detection is to recognize the element or find the occurrence of interest in assembling the suspected outlines. Where the object is shaped by a unique directional method or method to capture the shape in the coincident edges. The image obtained from the dataset is a variety of edges. Where the basic box graph of element detection and its sequel is shown in Figure 2 [12-18].

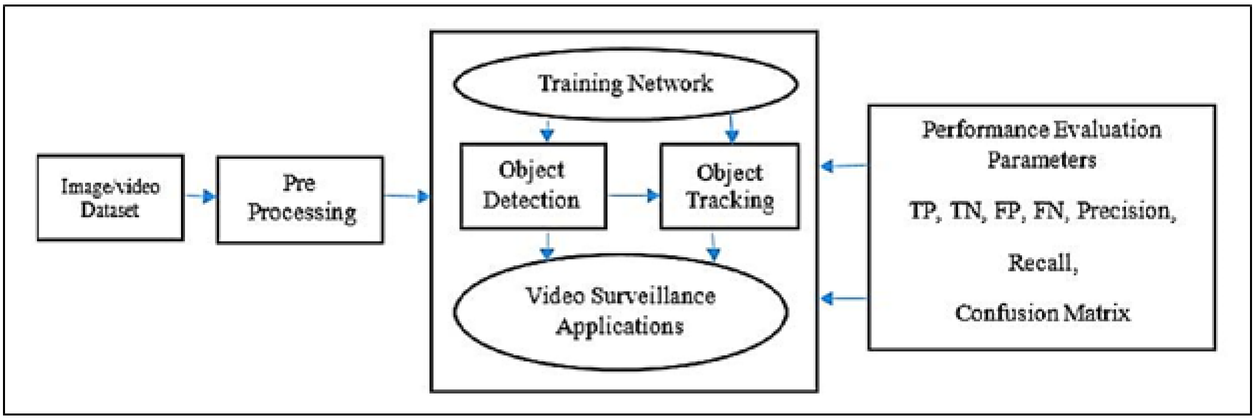

Figure 2: Object recognition and tracking block diagram [12-18].

The information set is separated towards double sections. 80% of the images in the dataset are used for preparation and 20% for examination. Image recognition is also done to track the shapes in it using CNN techniques calculations with YOLOv3 [19, 20]. The jump box is composed along the figure vs. the over-link (IoU) > 0.5. The recognized bounce box is transmitted as sources to the brain networks that support it to obtain the tracking. Finite edges are tracked simultaneously using multi-object tracking (MOT). The significant of such exploration mission is employed in computing traffic density at rush hour traffic intersections, in autonomous vehicles to identify various kinds of components with fluctuating enlightenment, also in optimizing smart city and smart vehicle frameworks.

2. Literature review

Various studies and references connected with the issues of multi-reason mobile robots in view of microcontrollers and remote innovation have been gotten to in the references. In this segment, we will audit the latest distributions and articles connected with this title, additionally summing up them constantly of distribution. About getting a wide-ranging opinion as accessible with the most recent multi-reason mechanical upgrades with refreshes that address such points, as opposed to building a coordinated idea to foster the examination issue likewise to settle the targets and show up at the supportability of this survey, as well as to propose feasible outcomes with the examination permitted in this Survey. This section provides an overview of various studies addressing the tasks of autonomous driving and object tracking by mobile robots that endowed with the ability to independently track objects, have become indispensable in diverse industries. While there have been notable advances in tracking methods for mobile robots, challenges remain, such as managing occlusions, navigating dynamic environments, and ensuring prompt responsiveness. The tracking of objects relies on attributes like color, external shape, and size, generating synthetic datasets that researchers in the autonomous vehicles and tracking domain heavily depend on to assess the efficacy of machine learning algorithms. Using color tracking of objects, there are some studies that have dealt with this type of tracking. The most recent articles and exploration covering the functioning title are recorded underneath: In 2021, Vagale, A., et. al., [8], algorithms that don't need map portrayal (progressed) and those that do (exemplary) have been introduced as a charming division in robot development control. High level delicate registering with inspecting depended algorithms is taken care of by the customary method which contains diagram research draws near. In 2013, Souissi, O., et. al., [9], proposed a few self-evident and reasonable classes for route planning: depended on the robot model (complete, non-all out, kinematic); likewise founded on the guide model's requests (whether they were determined ahead of time); depending on the capacity to remap (disconnected or associated). In addition, under basic development criteria (deterministic or probabilistic), it is checked whether the calculation reliably shows a similar arrangement. In 2012, Jeong, S., et. al., [10], it has been exhibited and explored how surface mobile robots could go starting with one area in space then onto the next. Thus, the route planner ought to consider how the movement plan will cooperate with such a surface. A few algorithms, for example, require the making of a diagram that precisely portrays the setting with the end goal that the robot is working. Diagram Search algorithms, that fall underneath the C-Space search classification, ordinarily show this. The outline could likewise be used by transformative algorithms like Ant Colony Optimizers (ACO). This resource could address how the spatial course of action of the situation's route is impacted by territory features. In particular, the chart being referred to is proposed to be depended on measurement maps here, however another guides sorts, like topological and semantic guides, are past the extent of this review. In, 2013, Nash, A., et. al., [11], introduced a grouping of way maps that are better-figured out because of crafted by those specialists. Such exploration showed and made sense of that it recognizes guides and cell examination. The surface mosaic of the initial two cells is framed. Networks, whether standard or irregular, could be used to orchestrate such cells. In 2020, Bergman, K., et. al., [12], the movement of robots was analyzed using vision charts and cross section state diagrams. The last option includes causing Edges to depend on movement replacements, guaranteeing that the subsequent way is attainable because of bot development limitations, especially while utilizing chart search algorithms. Such diagrams' cells or hubs could store static or dynamic components of information about the surface at their positions. This may be, for example, determined as data concerning rise. In 2020, Effati, M., et. al., [17], investigated the robot's movement setup as a subject of exploration. Coming up next are important for the different kinetic and dynamic models that the analysts checked on in this study which derived by differential. The base turning sweep of robots with Front Ackermann steering and the high energy utilization of slide steering robots through turning maneuvers are two instances of imperatives that are relevant to way arranging. In 2015, Brunner, M., et. al., [19], explored a few kinematic designs to allow the robot to give the Point Turn move, which makes them to spin past transmission. It is an advantage to relate the event of explained robots that are fit for inward plotting to acquire a piece of sort of advantage too give various sorts of locomotion. The explained robots, against tracks, for example, could proficiently control their dependability while steering on rough terrains. In 2019, Sánchez-Ibánez, J.R., et. al., [20], recognized the reconfiguration capacity of way arranging algorithms are really important for such robot kind, as they could find gets to that take advantage of their colossal versatility. In the issue of worldwide preparation, the creators used a Chart Search calculation, Dijkstra, to design an entrance and afterward, by reproduction hardware, process that locomotion made is ideal to move each piece of its segments. Subsequently, the creators of such review distribution proposed the execution of a PDE assessment technique to respect the multi-locomotion models using an isotropic expense capability at the instant of planning. In 2017, Norouzi, M., et. al., [21], proposed the execution of the Quick Walking Tree (FMT), the Inspecting Based calculation, to handle the inspiration planning of a re-plotted wheeled-legs hybrid robot. The locomotion of the robot will adjust best or more awful depending on the territory properties. Such attitudes may be reliant upon either the morphology (design) or the territory arrangement. One of such element is the slant or landscape tendency. The incline influences the robot's Roll and Pitch orientation points, which is important to be respected for soundness safeguarding. In 2019, Shokoohinia, M.R., et. al., [22], a control regulation for eyewitness responses has recommended depending on the limited component approach with model minimization. Concerning robustness, among the control methods, the sliding mode controller (SMC) is a simple methodology, which delineates security against non-model boundary varieties outer dynamics as well as unsettling influences. In 2017, Rsetam, K., et. al., [23], a progressive non-peculiarity station SMC has recommended, which could guarantee a quicker intermingling rate to zero of framework states inside for a limited period and peculiarity free. In 2019, Soltanpour, M.R., et. al., [24], a voltage-based SMC is recommended, that has low computational volume. In spite of the intrinsic advantages of robustness contrasted with aggravations, the presentation of SMCs might be impacted by changing framework boundaries. In 2020, Mahmoodabadi, M., et. al., [25], utilized a strategy to deal with change nonlinear dynamics towards linear dynamics; hence, a sliding position control technique has executed as a way following controller. Strange model is utilized to control the increase of the control center. In 2019, Zaare, S., et. al., [26], a voltage-subordinate sliding mode is considered where the controller is joined with a versatile assessor. The control unit that could be manipulated and work the vulnerabilities on the heap side and the drive side at the specific time frame is as yet absent. In 2021, Tuan, H.M., et. al., [27], executed the controller on a two DOFs robot arm with adaptable actuators. What's more, a versatile control is portrayed that expects to settle the model and furthermore manage vulnerabilities for the impact of outside force/torque not delivered. In 2021, Hao, N.V., et. al., [28], extended the examination by giving further reproduction tries and proposing new algorithms to further develop the control cycle. A correlation was formed with a conventional sliding mode controller to show the viability of the proposed calculation. In paper [27] the authors present the control system of a mobile robot designed for educational purposes, capable of detecting, tracking, and following an object of a specific color. The robot is controlled using a Raspberry Pi development system and is equipped with a video camera connected to it object detection and location. Image acquisition and processing are done in real time using control program written in Python language. Additionally, a graphic display connected to the Raspberry Pi board facilitates tracking of the processed images. The paper also discusses the implementation of a numerical control algorithm used for object tracking, in [28] the researchers contributes to the field by using the CIE L a b color space for detecting a red circle captured by the RGB-D camera on the mobile robot. The perceived red circle's diameter information is used for the movement action of the mobile robot platform, another group of researchers [29] presents a prototype of a mobile robot for object tracking that utilizes sensor vision, specifically the Pixy CMU Cam5, to recognize and track objects based on color. The robot is equipped with a DC motor for locomotion and an Arduino UNO microcontroller for processing and controlling the robot's movements. The system combines both hard components and soft components. The tests conducted show that the DC motor can move according to specifications and the Pixy sensor vision can accurately capture pixels of well-configured colors, another study [30] proposes a new algorithm that combines distance sensors and a vision sensor to assist a mobile robot in navigating through a maze and tracking colored objects, this algorithm is tested using the Mobile Robotics Simulation Toolbox in Matlab, and the simulation results demonstrate the successful tracking and locating of a colored object without collision with obstacles. One of the common ways to track things is the deep learning method. In study [31], pre-trained and tested deep learning models named SSD and YOLO are adopted for object detection and localization. The detection models are also integrated with different tracking algorithms, including GOTURN, MEDIANFLOW, TLD, KCF, MIL, and BOOSTING. These algorithms help track and predict the trajectories of detected objects. These models achieved tracking accuracy ranging from 90% to 94%. In [32], other researchers have presented another deep learning method for tracking objects by adopting the ConvNet-LSTM function approximator for direct prediction. For successful training, a personalized reward function and environmental reinforcement technology are used. This system can recover tracking after losing the tracked target from time to time, other authors proposes in paper [33] a robot grasping method based on deep learning target detection to address the high error rate of target recognition and low success rate of grasping, the method involves investigating the robotic arm hand-eye calibration and using the Basler camera as the visual perception tool. The AUBO i10 robot arm is used as the main body of the experiment, and the PP-YOLO deep learning algorithm is employed for target detection and poses estimation, experimental data collection and grasping experiments on randomly placed targets in real scenes were conducted. The results showed a 94.93% success rate of grasping target detection and a 93.37% success rate of robot grasping. There are other studies that use different methods to track objects. In the study [34] the authors proposes a fully-connected Siamese network tracking method for object tracking in mobile robots, which uses histogram of gradient feature similarity and fading-memory Kalman filter for real-time correction and compensation. It enables the robot to track the target accurately even when it is occluded or temporarily lost. This document [35] introduces a process that integrates object detection and tracking to swiftly identify and trail an individual in real-time through the use of a stereo camera. The results achieved are comparable to leading person-tracking systems. The process employs robust person detection through deep convolutional neural networks and incorporates trackers to maintain the identity of the target individual. Additionally, it is designed to optimize performance for devices with constrained computing power. The paper [36] focuses on the detection and tracking algorithm of a robot moving target using a Laser Range Finder. It uses real-time information from the Laser Range Finder to calculate and predict the movement state of the target, and fits a control function to enable the robot to track the target in real-time. Experiments conducted on the AS-R robot platform show that the control algorithm effectively tracks the moving target and has good robustness. The authors of [37] presents a vision-based approach using a wireless camera to detect and track objects in the field of view of a mobile security robot, independent of lighting conditions. The proposed system utilizes the Principle Component Analysis (PCA) algorithm and filters to implement and demonstrate the image processing process, with an attention system for frame tracking and estimating the position of a person. The study [38] presents a novel visual servo tracking method for a wheeled mobile robot that combines target features and depth information of the scene, he proposed method consists of two phases: the first phase uses feature matching to bring the target into the field of vision, and the second phase implements visual servo aiming for accurate object tracking. The method also incorporates depth information to reduce computational complexity and includes a mechanism for detecting and exiting local minimums. Experimental results demonstrate the feasibility and effectiveness of the two-phase method, which is capable of sequentially tracking multiple objects. In the research [39] objects are tracked by an optical tracking system by identifying the object and estimating its position using image processing. The camera installed on the robot moves in four directions. The results showed that the movement of the camera tracking the object under it produced a greater angular error compared to its movement in any other direction, despite the same distance between the object in any direction and the camera. In [40] targets are tracked using an algorithm based on Model Predictive Control (MPC). The importance of this work lies in incorporating nonlinear potential field functions as constraints within a convex optimization framework. This method identifies non-convex constraints and dependencies, by replacing them with pre-computed external input forces. The proposed algorithm also includes different obstacle avoidance methods using potential field functions in the layout. The researchers proposed a path planning algorithm for intelligent mobile robots based on lidar-based dynamic target detection, which can quickly find optimal or approximate optimal planning paths in both dynamic and static environments in [41]. The paper [42] introduces planning algorithms for multi-target tracking with multiple robots that are resilient to failures, such as attacks or sensor failures. It provides the first scalable algorithm for resilient target tracking, which achieves maximal resiliency and terminates with the same running time as state-of-the-art algorithms for non-resilient target tracking. The algorithm guarantees a solution that is close to optimal and quantifies its approximation performance using a novel notion of curvature for monotone set functions subject to matroid constraints. The authors in research [43] investigate the method of object recognition and autonomous obstacle avoidance for mobile robots using vision-based sensors by build a mobile platform equipped with a Kinect sensor and laser rangefinder sensor, and use the SURF algorithm for target feature extraction and the RANSAC algorithm for optimization, the experiment proves the effectiveness of the system in completing the tasks of target recognition and autonomous obstacle avoidance. Other team in the paper [44] discussed development of an ultrasonic line follower robot that can detect obstacles and edges for industrial and rescue operations. It proposes using infrared sensors to detect visible lines embedded in the ground, and ultrasonic sensors to detect obstacles and edges. The robot is designed to stop and not pass obstacles until they are removed, and it can also identify front edges. The goal of the study is to create a monitoring system that can follow specific paths and detect objects and edges using ultrasonic frequencies. The robot has potential applications in commercial, medical, rescue, and military operations. The paper [45] proposes a vision-based feedback method combined with an explicit control method for leader-follower robot formation in object transportation tasks. The experimental results suggest that the vision-based feedback method is more effective in cooperative object carrying tasks. The study [46] proposes an Edge Computing-based Multivariate Time Series (EC-MTS) framework for accurate mobile object tracking in IoT systems, which offloads computation tasks from energy-constrained IoT devices to edge computing infrastructure. The framework utilizes statistical technique (vector auto regression) to fit a trajectory model for accurate location prediction of mobile objects. Experimental results demonstrate that the EC-MTS framework significantly improves mobile object tracking efficacy in terms of trajectory goodness-of-fit and location prediction accuracy. Additionally, the paper extends the framework to enable multiple objects tracking in IoT systems.

3. Bayesian filter

One of the most important techniques used to objects detection, which we will focus on in this research, is the Bayesian filter, as it can be used in nonlinear systems based on probability. In Bayes filtering, probability is essential for handling uncertainty by integrating prior knowledge and sensor data about a system. The Bayes filter's goal is to recursively determine the posterior probability distribution of the target's state, continually updating this distribution as new sensor evidence is received. This process allows for more accurate predictions and adjustments based on incoming information [47].

3.1 Probability in Bayesian Filters

- Prior Probability:

This represents our initial belief about the system's state before gathering any new measurements or data. It reflects our understanding based on prior information or existing models and serves as the starting point for our knowledge of the system's state.

- Likelihood:

This term measures the probability of obtaining a specific measurement given the current state of the system. It is crucial for updating our beliefs with new data. Simply put, it answers the question: "Based on our current understanding of the system's state, how likely is this measurement?"

- Posterior Probability:

This represents our updated belief about the system's state after incorporating new measurement data. It merges our prior knowledge (the prior probability) with the new evidence (the likelihood), providing the most current and accurate estimate of the system's state based on all available information.

In summary, we begin with the "prior probability" as our initial assumption. When new measurements come in, we use the "likelihood" to determine how probable those measurements are given our current state estimate. By merging these two, we obtain the "posterior probability," which is our updated and refined estimate of the system's state [48].

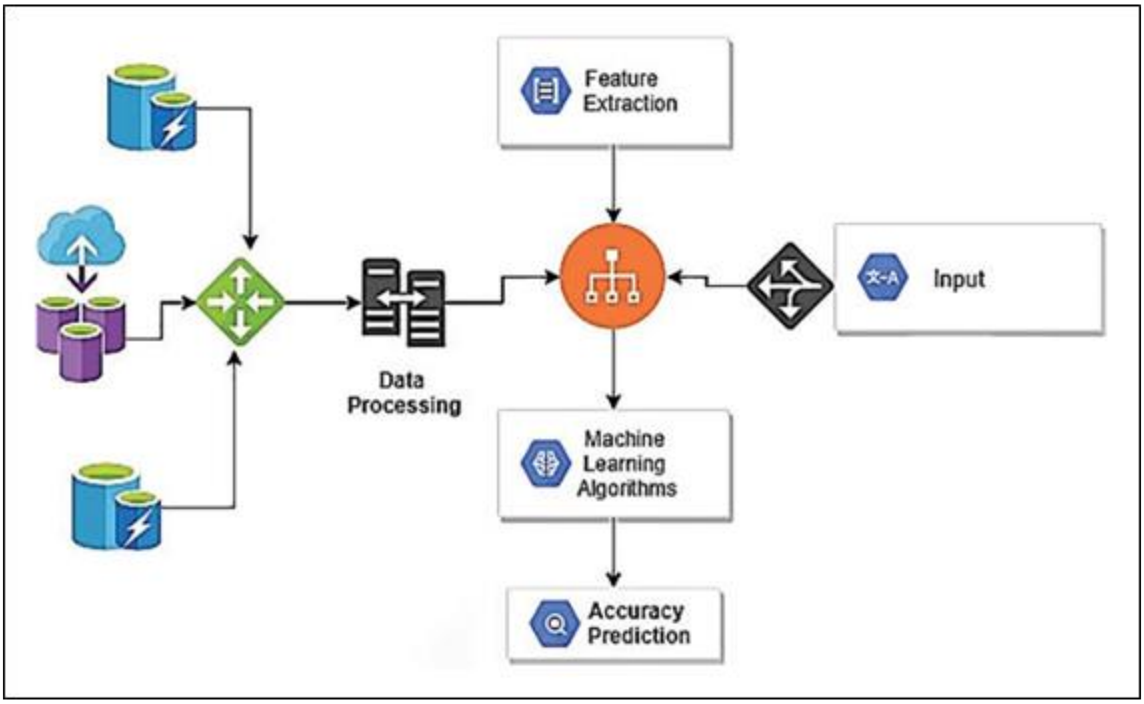

Figure 3: Comprehensive overview of machine learning-based accuracy prediction using a Bayesian probabilistic model [49]

3.2 Bayes' Theorem:

Bayes' Theorem, named after Thomas Bayes, calculates the belief in quantity A based on knowledge of quantity B. It starts with the prior probability P(A), representing the initial belief in A without additional evidence. The conditional probability P(B|A) indicates the likelihood of observing B if A is true. By applying Bayes' rule, the theorem updates this belief to determine the posterior probability, which is the likelihood that hypothesis A is true given the observation B. This method allows for refined predictions as new evidence is obtained [47]. Mathematically, it's expressed as:

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)}$$

Where

P(A | B): Posterior probability of A given B. P(B | A): Likelihood of B given A. P(A): Prior probability of A. P(B): Probability of B (normalizing constant).

Bayesian filters predict the state of a dynamic system over time by using sequential measurements (data). They encompass various types:

- Kalman Filters: The Kalman filter, introduced by R.E. Kalman in 1960, is a widely recognized Bayesian estimation technique. It assumes Gaussian distributions and a linear state space model. As an optimal recursive method, it minimizes the error covariance in state estimation by applying Bayesian prediction and correction steps. This filter provides an exact solution for estimating the target state with minimal error in linear Gaussian state space models [50,51].
- Extended Kalman Filters (EKF): The Extended Kalman Filter (EKF) is a variant of the Kalman filter used for tracking a target vehicle's position and speed. It addresses nonlinear systems by linearizing them with Jacobian matrices. EKF forecasts the system's next state using the current state and sensor measurements, such as radar and LiDAR data. In this study

[52, 53], the EKF was enhanced with a reliability function that accounts for the distance characteristics of sensors, thereby improving position estimation accuracy. This function reduces errors from inaccurate sensor measurements by incorporating the distance characteristics of LiDAR and radar sensors [51].

- Particle Filters: Particle filtering is a versatile framework utilized in tracking applications, adept at integrating diverse observation models and motion priors to probabilistically assess uncertainty in tracking outcomes. Effective tracking performance hinges on a robust observation model, while the efficiency of particle sampling and evaluation dictates the tracking frame rate. Deep neural networks are leveraged in this framework to enhance accuracy in estimating object orientations, especially in challenging scenarios like occlusions. By employing random particles weighted according to importance, particle filters excel in handling nonlinear systems, offering optimal estimates of state variables. This capability makes them particularly valuable for addressing nonlinear and non-Gaussian challenges across various domains, including target tracking and signal processing [51, 54, 55].

3.3 Detection by using Bayes filter algorithm

Detection using the Bayes filter algorithm typically refers to the process of estimating the state of a system based on noisy measurements. The Bayes filter is particularly useful in scenarios where there is uncertainty and noise in both the measurements and the dynamics of the system itself. Here's a breakdown of the equations involved in the Bayes filter algorithm, commonly used in applications like tracking objects in computer vision or estimating parameters in sensor networks:

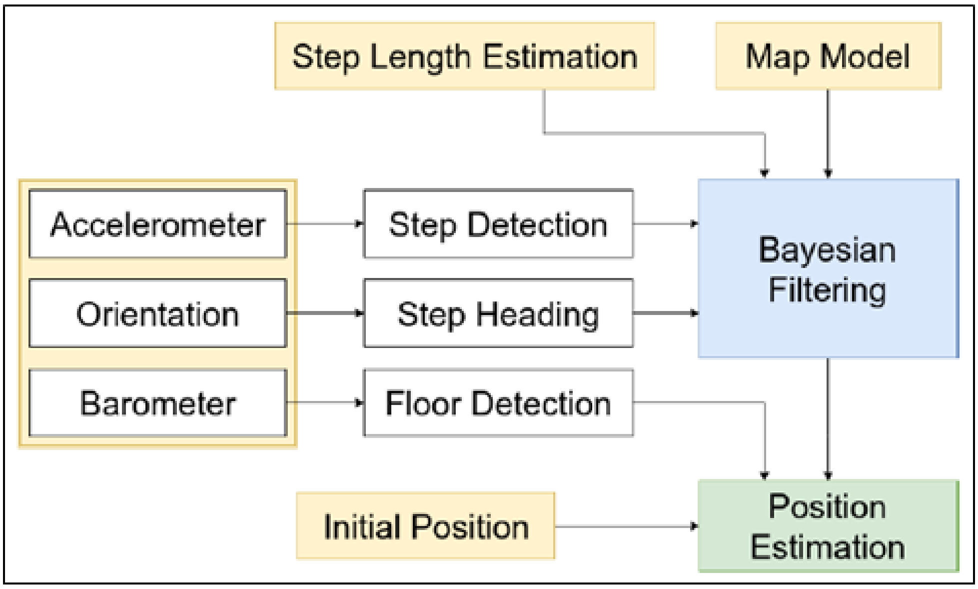

Figure 4: Evaluate different implementations of Bayesian filtering [56].

3.4 Bayesian Filter Equations

1. State Prediction (Prior Estimate):

$$\bar{x}_t = \int p(x_t|u_t, x_{t-1}).x_{t-1}dx_{t-1}$$

This equation predicts the system's state at time t based on the prior state x_{t-1} and the control input u_t.$p(x_t \mid u_t, x_{t-1})$. It serves as the transition or motion model, detailing how the state changes over time.

2. Measurement Update (Posterior Estimate):

$$x_t = \int p(x_t|z_t, \bar{x}_t).\bar{x}_t d\bar{x}_t$$

Upon receiving a measurement z_t, this equation refines the predicted state $\bar{x}_t$ to a more accurate estimate. The measurement model or likelihood function, represented by $\bar{x}_t.(x_t|z_t,\bar{x}_t)$, describes the probability of obtaining measurement z_t given the state x_t.

3. Bayes' Filter Formula:

$$\mathrm{bel}(x_t) = \eta . p(z_t|x_t). \int p(x_t|u_t, x_{t-1}). \mathrm{bel}(x_{t-1}) dx_{t-1}$$

This formula integrates the prediction and update steps to determine the belief state $\mathrm{bel}(x_t)$, which represents the posterior probability distribution of the state xt given all measurements up to time t. In this context, η is the normalization constant that ensures the belief state $\mathrm{bel}(x_t)$ sums to 1.

3.5 Steps in Bayes Filter Algorithm

- Initialization: Start with an initial belief state $\mathrm{bel}(x_0)$.
- Prediction: Use the motion model $p(x_t \mid u_t, x_{t-1})$ to predict the state.
- Measurement Update: Incorporate the measurement z_t using the measurement model $p(z_t \mid x_t)$ to update the state estimate.
- Normalization: Ensure the belief state $p(z_t \mid x_t)$ is normalized after each update.

The Bayes filter is crucial in many probabilistic robotics and sensor fusion applications, offering a systematic method to manage uncertainty and enhance state estimation over time.

4. Conclusion

The previous studies provided a comprehensive overview of autonomous driving and object tracking by mobile robots. The authors explore innovative approaches to enhance object detection accuracy through the utilization of advanced techniques such as deep learning architectures, feature engineering, and optimization filters algorithms. The proposed methods have shown promising results in improving the accuracy of object detection and tracking, which can have significant implications for various industries such as autonomous vehicles, surveillance, and robotics. However, challenges remain, such as managing occlusions, navigating dynamic environments, Tracking moving targets, and ensuring prompt responsiveness. Overall, this research highlights the use of Bayesian filtering algorithm as a new method in the field of object detection and tracking to improve the accuracy and efficiency of computer vision systems.

5. References

1. Sutoh, M.; Otsuki, M.; Wakabayashi, S.; Hoshino, T.; Hashimoto, T. The right path: Comprehensive path planning for lunar exploration rovers. IEEE Robot. Autom. Mag. 2015, 22, 22–33.
2. Inotsume, H.; Creager, C.; Wettergreen, D.; Whittaker, W. Finding routes for efficient and successful slope ascent for exploration rovers. In Proceedings of the 13th International Symposium on Artificial Intelligence, Robotics and Automation in Space (i-SAIRAS), Beijing, China, 19–22 June 2016; pp. 1–10.
3. Inotsume, H.; Kubota, T.; Wettergreen, D. Robust Path Planning for Slope Traversing under Uncertainty in Slip Prediction. IEEE Robot. Autom. Lett. 2020, 5, 3390–3397.
4. Niksirat, P.; Daca, A.; Skonieczny, K. The effects of reduced-gravity on planetary rover mobility. Int. J. Robot. Res. 2020, 39, 797–811.
5. Plonski, P.A.; Tokekar, P.; Isler, V. Energy-efficient path planning for solar-powered mobile robots. J. Field Robot. 2013, 30, 583–601.
6. Kaplan, A.; Kingry, N.; Uhing, P.; Dai, R. Time-optimal path planning with power schedules for a solar-powered ground robot. IEEE Trans. Autom. Sci. Eng. 2016, 14, 1235–1244.

7. Groves, K.; Hernandez, E.; West, A.; Wright, T.; Lennox, B. Robotic Exploration of an Unknown Nuclear Environment Using Radiation Informed Autonomous Navigation. Robotics 2021, 10, 78.
8. Vagale, A.; Oucheikh, R.; Bye, R.T.; Osen, O.L.; Fossen, T.I. Path planning and collision avoidance for autonomous surface vehicles I: A review. J. Mar. Sci. Technol. 2021, 26, 1292–1306.
9. Souissi, O.; Benatitallah, R.; Duvivier, D.; Artiba, A.; Belanger, N.; Feyzeau, P. Path planning: A 2013 survey. In Proceedings of the 2013 International Conference on Industrial Engineering and Systems Management (IESM), Rabat, Morocco, 28–30 October 2013; pp. 1–8.
10. Yi, C.; Jeong, S.; Cho, J. Map representation for robots. Smart Comput. Rev. 2012, 2, 18–27.
11. Nash, A.; Koenig, S. Any-angle path planning. AI Mag. 2013, 34, 85–107.
12. Bergman, K.; Ljungqvist, O.; Axehill, D. Improved path planning by tightly combining lattice-based path planning and optimal control. IEEE Trans. Intell. Veh. 2020, 6, 57–66.
13. Huang, H.P.; Chung, S.Y. Dynamic visibility graph for path planning. In Proceedings of the 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No. 04CH37566), Sendai, Japan, 28 September–2 October 2004; Volume 3, pp. 2813–2818.
14. Petres, C.; Pailhas, Y.; Petillot, Y.; Lane, D. Underwater path planing using fast marching algorithms. In Proceedings of the Oceans 2005-Europe, Brest, France, 20–23 June 2005; Volume 2, pp. 814–819.
15. Papadakis, P. Terrain traversability analysis methods for unmanned ground vehicles: A survey. Eng. Appl. Artif. Intell. 2013, 26, 1373–1385.
16. Zhang, H.; Zhang, Y.; Yang, T. A survey of energy-efficient motion planning for wheeled mobile robots. Ind. Robot. Int. J. Robot. Res. Appl. 2020, 47, 607–621.
17. Effati, M.; Fiset, J.S.; Skonieczny, K. Considering slip-track for energy-efficient paths of skid-steer rovers. J. Intell. Robot. Syst. 2020, 100, 335–348.
18. Patel, N.; Slade, R.; Clemmet, J. The ExoMars rover locomotion subsystem. J. Terramech. 2010, 47, 227–242.
19. Brunner, M.; Fiolka, T.; Schulz, D.; Schlick, C.M. Design and comparative evaluation of an iterative contact point estimation method for static stability estimation of mobile actively reconfigurable robots. Robot. Auton. Syst. 2015, 63, 89–107.
20. Sánchez-Ibánez, J.R.; Pérez-del Pulgar, C.J.; Azkarate, M.; Gerdes, L.; García-Cerezo, A. Dynamic path planning for reconfigurable rovers using a multi-layered grid. Eng. Appl. Artif. Intell. 2019, 86, 32–42.
21. Norouzi, M.; Miro, J.V.; Dissanayake, G. Planning stable and efficient paths for reconfigurable robots on uneven terrain. J. Intell. Robot. Syst. 2017, 87, 291–312.
22. Shokoohinia, M.R.; Fateh, M.M. Robust dynamic sliding mode control of robot manipulators using the Fourier series expansion. Trans. Inst. Meas. Control 2019, 41, 2488–2495. [CrossRef]
23. Rsetam, K.; Cao, Z.; Man, Z. Hierarchical non-singular terminal sliding mode controller for a single link flexible joint robot manipulator. In Proceedings of the IEEE 56th Annual Conference on Decision and Control (CDC), Melbourne, VIC, Australia,12–15 December 2017; pp. 6677–6682.

24. Soltanpour, M.R.; Moattari, M. Voltage based sliding mode control of flexible joint robot manipulators in presence of uncertainties. Robot. Auton. Syst. 2019, 118, 204–219.

25. Mahmoodabadi, M.; Nejadkourki, N. Trajectory Tracking of a Flexible Robot Manipulator by a New Optimized Fuzzy Adaptive Sliding Mode-Based Feedback Linearization Controller. J. Robot. 2020, 2020, 8813217. [CrossRef]

26. Zaare, S.; Soltanpour, M.R.; Moattari, M. Adaptive sliding mode control of n flexible-joint robot manipulators in the presence of structured and unstructured uncertainties. Multibody Syst. Dyn. 2019, 47, 397–434. [CrossRef]

27. Tuan, H.M.; Sanfilippo, F.; Hao, N.V. An Adaptive Sliding Mode Controller for a 2-DOF Elastic Robotic Arm. In Proceedings of the 4th International Conference on Intelligent Technologies and Applications (INTAP 2021), Grimstad, Norway, 11–13 October 2021.

28. Tuan, H.M.; Sanfilippo, F.; Hao, N.V. Modelling and Control of a 2-DOF Robot Arm with Elastic Joints for Safe Human-Robot Interaction. Front. Robot. AI 2021, 8, 679304. [CrossRef]

29. Raghavan, V.S.; Kanoulas, D.; Laurenzi, A.; Caldwell, D.G.; Tsagarakis, N.G. Variable configuration planner for legged-rolling obstacle negotiation locomotion: Application on the centauro robot. In Proceedings of the 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, 4–8 November 2019; pp. 4738–4745.

30. Otsu, K.; Matheron, G.; Ghosh, S.; Toupet, O.; Ono, M. Fast approximate clearance evaluation for rovers with articulated suspension systems. J. Field Robot. 2020, 37, 768–785.

31. Hines, T.; Stepanas, K.; Talbot, F.; Sa, I.; Lewis, J.; Hernandez, E.; Kottege, N.; Hudson, N. Virtual Surfaces and Attitude Aware Planning and Behaviours for Negative Obstacle Navigation. IEEE Robot. Autom. Lett. 2021, 6, 4048–4055.

32. Taghavifar, H.; Rakheja, S.; Reina, G. A novel optimal path-planning and following algorithm for wheeled robots on deformable terrains. J. Terramech. 2020, 96, 147–157.

33. Arvidson, R.E.; Bell, J.; Bellutta, P.; Cabrol, N.A.; Catalano, J.; Cohen, J.; Crumpler, L.S.; Des Marais, D.; Estlin, T.; Farrand,W.; et al. Spirit Mars Rover Mission: Overview and selected results from the northern Home Plate Winter Haven to the side of Scamander crater. J. Geophys. Res. Planets 2010, 115, 1–19. [CrossRef]

34. Barabas, T., et al. Control System of an Autonomous Object Tracking Robot. in 2023 17th International Conference on Engineering of Modern Electric Systems (EMES). 2023. IEEE.

35. ATALI, G. and M. EYÜBOĞLU, A Study on Object Detection and Tracking of a Mobile Robot Using CIE L^* a^* b^* Color Space. Düzce Üniversitesi Bilim ve Teknoloji Dergisi, 2022. 10(5): p. 77-90.

36. Dewi, T.S., et al. Prototype of mobile robot tracking object using sensor vision. in 2022 8th International Conference on Wireless and Telematics (ICWT). 2022. IEEE.

37. Aldair, A.A. and A. Al-Mayyahi, Maze Maneuvering and Colored Object Tracking for Differential Drive Mobile Robot. Iraqi J. Electr. Electron. Eng, 2019. 15(1): p. 47-52.

38. Ahmed, I., et al., Towards collaborative robotics in top view surveillance: A framework for multiple object tracking by detection using deep learning. IEEE/CAA Journal of Automatica Sinica, 2021. 8(7): p. 1253-1270.

39. Luo, W., et al., End-to-end active object tracking and its real-world deployment via reinforcement learning. IEEE transactions on pattern analysis and machine intelligence, 2019. 42(6): p. 1317-1332.

40. Zhao, W., B. Xu, and X. Wu. Robot grasping system based on deep learning target detection. in Journal of Physics: Conference Series. 2023. IOP Publishing.

41. Chen, L., et al. A Robust Object Tracking and Visual Servo Method for Mobile Robot. in 2022 IEEE International Conference on Real-time Computing and Robotics (RCAR). 2022. IEEE.
42. Agrawal, K. and R. Lal, Person following mobile robot using multiplexed detection and tracking, in Advances in Mechanical Engineering: Select Proceedings of ICAME 2020. 2020, Springer. p. 815-822.
43. Lu, C.-g., J.-x. Wang, and X. Cui. Moving Target Tracking with Robot Based on Laser Range Finder. in 2020 5th International Conference on Automation, Control and Robotics Engineering (CACRE). 2020. IEEE.
44. Salih, T.A., M.T. Ghazal, and Z.G. Mohammed, Development of a dynamic intelligent recognition system for a real-time tracking robot. IAES International Journal of Robotics and Automation, 2021. 10(3): p. 161.
45. Liu, C.-Y., Z.-W. Chang, and C.-L. Chen. Visual servo tracking of a wheeled mobile robot utilizing both feature and depth information. in 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA). 2019. IEEE.
46. Khairudin, M., et al., Control of a movable robot head using vision-based object tracking. International Journal of Electrical and Computer Engineering (IJECE), 2019. 9(4): p. 2503-2512.
47. Tallamraju, R., et al. Decentralized mpc based obstacle avoidance for multi-robot target tracking scenarios. in 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR). 2018. IEEE.
48. Hu, H. Research and analysis of robot path planning based on target detection. in International Conference on Mathematics, Modeling, and Computer Science (MMCS2022). 2023. SPIE.
49. Zhou, L., et al., Resilient active target tracking with multiple robots. IEEE Robotics and Automation Letters, 2018. 4(1): p. 129-136.
50. Zhang, L. and D. Li, Research on mobile robot target recognition and obstacle avoidance based on vision. Journal of Internet Technology, 2018. 19(6): p. 1879-1892.
51. Barua, V., et al., An ultrasonic line follower robot to detect obstacles and edges for industrial and rescue operations. International Journal of Computer Applications, 2020. 176(31): p. 31.
52. Jayarathne, D., et al. Vision-based Leader-Follower Mobile Robots for Cooperative Object Handling. in 2019 19th International Conference on Control, Automation and Systems (ICCAS). 2019. IEEE.
53. Wu, Y., et al., Edge computing-based mobile object tracking in internet of things. High-Confidence Computing, 2022. 2(1): p. 100045.
54. Ishigami, G.; Nagatani, K.; Yoshida, K. Path planning for planetary exploration rovers and its evaluation based on wheel slip dynamics. In Proceedings of the 2007 IEEE International Conference on Robotics and Automation, Rome, Italy, 10–14 April 2007; pp. 2361–2366.
55. Stone, L.D., et al., Bayesian multiple target tracking. 2013: Artech House.
56. Rohmer, J., Uncertainties in conditional probability tables of discrete Bayesian Belief Networks: A comprehensive review. Engineering Applications of Artificial Intelligence, 2020. 88: p. 103384.
57. Karthik, S., et al., Prognostic Kalman Filter Based Bayesian Learning Model for Data Accuracy Prediction. Computers, Materials & Continua, 2022. 72(1).

58. Gurajala, R., et al. Derivation of the Kalman filter in a Bayesian filtering perspective. in 2021 2nd International Conference on Range Technology (ICORT). 2021. IEEE.

59. Särkkä, S. and L. Svensson, Bayesian filtering and smoothing. Vol. 17. 2023: Cambridge university press.

60. Kim, T. and T.-H. Park, Extended Kalman filter (EKF) design for vehicle position tracking using reliability function of radar and lidar. Sensors, 2020. 20(15): p. 4126.

61. Särkkä, S., Recursive Bayesian inference on stochastic differential equations. 2006: Helsinki University of Technology.

62. Deng, X., et al., PoseRBPF: A Rao–Blackwellized particle filter for 6-D object pose tracking. IEEE Transactions on Robotics, 2021. 37(5): p. 1328-1342.

63. Zeng, N., et al., An improved particle filter with a novel hybrid proposal distribution for quantitative analysis of gold immunochromatographic strips. IEEE Transactions on Nanotechnology, 2019. 18: p. 819-829.

64. Opiela, M. and F. Galčík, Grid-based Bayesian filtering methods for pedestrian dead reckoning indoor positioning using smartphones. Sensors, 2020. 20(18): p. 5343.