A Particle Filter Based Visual Object Tracking: A Systematic Review of Current Trends and Research Challenges

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***Abstract*—Visual object tracking is a crucial research area in computer vision because it can simulate a dynamic environment with non-linear motions and multi-modal non-Gaussian noises. However, This paper presents an overview of the recent developments in particle filter-based visual object tracking algorithms and discusses the pros and cons of particle filters, respectively. There are presentations of many different methodologies and algorithms in the research literature. The majority of visual object tracking research at present is on particle filters. In addition, the most advanced technique for visual object tracking has also been developed by combining the convolutional neural network (CNN) and the particle filter. The advantage of particle filters is that they can handle nonlinear models and non-Gaussian advancements, sequentially concentrating on the areas of the state space with higher densities, primarily parallelization, and simplicity of implementation. Despite this, it offers a robust framework for visual object tracking because it incorporates uncertainty and outperforms other filters like the Kalman filter, Kernelized correlation filter, optical filter, mean shift filter, and extended Kalman filter in recognition tests. In contrast, this study provided information on various particle filter features and classifiers.**

***Keywords*—Particle filter; visual object tracking; On-Gaussian noises; Kalman filter; CNN**

I. Introduction

In the last decade, object tracking has been a difficult research challenge in computer vision for video sequences, with applications including video surveillance, human-computer interaction, augmented reality, and robotics. However, particle filters (PFs) have recently gained popularity in visual object tracking. The ability to resolve non-Gaussian and non-linear problems allowed them to establish a reliable tracking method.

Tracking visual objects involves object recognition, classification, and frame-by-frame tracking. Identifying moving objects in a video stream is the first essential step in tracking. However, in addition to deep learning and CNN, various techniques such as background reduction, statistical models, and specific temporal techniques are applied for object detection. In order to keep track of and analyze observed objects, it is necessary to classify them, such as people, vehicles, animals, debris, etc. The second tracking stage is the creation of temporal connections between detected objects from frame to frame. The segmented regions can be identified temporally using this method, which also generates coherent information about the objects in the observed region, including their trajectory with direction and speed. Typically, the output of the tracking phase is used to assist and improve higher-level activity analysis, object classification, and motion segmentation.

Consequently, deterministic or stochastic frameworks can be used to classify object-tracking techniques. In addition to stochastic approaches, the Bayesian framework for state estimation incorporates stochastic approaches. In the stochastic framework, the Kalman filter [1], the extended Kalman filter, and the unscented Kalman filter [2] were used to estimate linear and Gaussian states. However, the particle filter (PF) [3], the condensation filter [4], and the bootstrap filter were used to estimate nonlinear and non-Gaussian states. Deterministic frameworks, such as mean shift [5], fragment-based tracker, and multi-stage tracker [6], use objective search in each frame to increase the similarity between the objective and search space. These techniques typically rely on less spatial information regarding the object, which makes them more susceptible to occlusion and background clutter [7]. However, stochastic approaches were able to address the problems caused by identical backgrounds and occlusion as well as large variations of a pose by decreasing target sampling patches throughout the track [8], [9].

Particle filters, a stochastic method, surpassed other methods for tracking objects in complex environments such as occlusion, background clutter, and illumination. These are used to estimate system states in state-space models; the system's various states are then tracked over time. By employing sequential Monte Carlo sampling, which uses a collection of samples known as particles to perform numerical approximation, particle filters can also solve the estimation problem. Additionally, particle filters demonstrate their effectiveness in overcoming various challenges associated with object tracking by performing exceptionally well with nonlinear and non-Gaussian estimation problems [4].

This paper's main contributions are summarized as follows:

(a) We present a comprehensive survey of particle filter-based visual object tracking techniques from different perspectives.
(b) We addressed the large-scale benchmark datasets for various visual object tracking approaches.
(c) We also summarize the state-of-the-art visual object tracking research over the past decade, including its advantages, limitations, and future directions.
(d) Finally, we offer some insightful observations and conclusions regarding the tracking of visual objects.

The remaining sections of the paper are organized as follows: The theoretical explanation of particle filters is briefly introduced in **Section II**. Visual object tracking with particle filter is discussed in **Section III**. However, in **Section IV**, benchmark datasets are detailed for visual object tracking. In **Section V**, the comparison techniques of visual object tracking using various PF. Finally, an extensive conclusion is outline in **Section VI**.

II. Particle Filter

Particle filter is a Monte Carlo and recursive Bayesian estimation-based filtering algorithm [10]. Particle filters exhibit superior performance compared to conventional methods such as the Kalman filter when applied to non-linear or non-Gaussian conditions. In addition, Particle filter is widely used in surveillance cameras, robotics, and navigation to track multiple objects using visual, geometric, and motion features, including color, texture, shape, outlines [13].

A particle filter is a Monte Carlo sampling approach for creating a recursive Bayesian filter [11], [12]. Particle filtering is a sampling technique that begins with a population of particles, each of which assigns no value to any variables. The goal of particle filter is to represent the posterior density with a set of random particles and weights, and then compute estimates the state variables' posterior density given the observation variables using these samples and weights. The particle filter is intended for use in a hidden Markov Model with both hidden and observable variables. The particle filter, sometimes known as the condensation filter, is a low-quality filter [15], [16].

The fundamental concept is that particle density distribution occurs when particles are sampled randomly. It is the most general Bayesian strategy since it has no restrictions on the state vector when dealing with nonlinear and non-Gaussian problems. The following is a description of how particle filters function. Based on a measure of probability, the state space is split into several parts, and each part is filled with particles. The higher the likelihood, the higher the particle concentration, according to the state equation, a particle system changes over time with the FPK equation determining the evolving pdf. By randomly selecting states from the state space, we produce a large number of particles that reflect the evolving pdf, because the point-mass histogram can approximate the pdf.

Particle filter technology's adaptability is a result of its dominance in nonlinear and non-Gaussian systems. The multi-modal processing abilities of the particle filter are another factor in the particle filter's widespread use. Particle filtering has been applied to numerous fields around the world. Fig. 1 below illustrates the core concept of the particle filtering (PF) technique.

Let, consider a system whose state changes over time, C_t= g(C_{t-1}, X_t), where C_t represents the current state of the system at time t. The state transition model g determines whether or not the system is $Markovian$. C_t is therefore dependent on the preceding state C_{t-1} as well as X_t is the system (process) dynamics, this enables the system to evolve over time. Imagine that part of the system is being observed using a set of noisy sensors S_t = z(C_t, Y_t). Where z describes the relationship between the sensor observations S_t, and current system state C_t with sensor noise Y_t of the observation model. Hence, X_t and Y_t's unpredictability is believed to be known and captured using $pdfs$ [14].

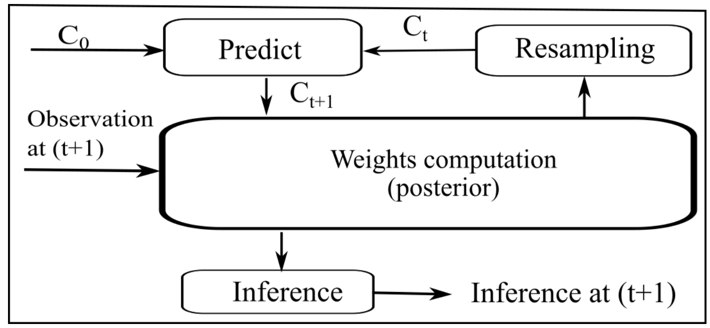

Fig. 1. The Workflow of the particle filter algorithm.

The particle filter algorithm consists of three major steps including selection, prediction, and measurement.

In first, we construct a new particle set in the selection step by picking the particles from the previous particle set with the highest posterior probability. By passing an object via a dynamic model, the prediction step tries to forecast how its state will change. The dynamic model has two functions: firstly, it disperses the state density through stochastic diffusion, and secondly, it causes the state density to drift in a deterministic fashion. Each particle is updated according to the state model during prediction, which includes the insertion of random noise to simulate the effect of the noise on the state. The weight of each particle is re-evaluated based on the new data in the measurement stage, and we estimate likelihood probability. In summary, the following is a description of the particle filter:

(a) The following are the system and measurement equations:

$$A_{k+1} = g_k(A_k, W_k) \, and \, B_k = h_k(A_k, V_k) \qquad (1)$$

Where the state variables vector A_k at time t are determined by a function g, with W_k and V_k being separate white noise processes with known $pdf's$. A function h connects the observations B_k with A_k.

(b) Let consider, the initial state of pdf $P(A_0)$ is known, produce N initial particles at random on the surface based on the pdf $P(A_0)$, where $A_{0,1} + (j = 1, ..., N)$ is the symbol for these particles. The user selects the parameter N as a compromise between computing effort and estimating precision.

(c) For k = 1, 2,..., do the following:

(1) Apply the known pdf with the known process equation of the process noise to the time propagation step to obtain the a priori particles a_k:

$$A^-_{k,j} = g_{k-1}(A^+_{k-1,j}, W^j_{k-1})(j = 1, \ldots .N) \qquad (2)$$

where each W^j_{k-1} noise vector is created at random using the known pdf of W_{k-1}.

(2) Calculate each particle's relative likelihood q_j, $A_{k,j}$ and conditional on B_k measurement. This is accomplished by calculating the pdf $p(B_K/A^-_{k,j})$ using the non-linear measurement equation and the measurement noise pdf.

(3) In the preceding step, scale the relative likelihoods as follows:

$$q_j = \frac{q_j}{\sum_{i=1}^{N}(q_i)} \tag{3}$$

Now add up all of the likelihood numbers is one.

(4) Using the relative likelihoods q_j, generate a collection of a posterior particles $A^+_{k,j}$. It is also called the re-sampling stage.

(5) Now that we have a collection of particles $A^+_{k,j}$ that are dispersed in accordance with the pdf of $p(A_k/B_k)$, any required statistical measure of the pdf can be calculated. However, calculating the mean and covariance is typically of significant concern.

III. Visual Object Tracking with Particle Filter

Visual tracking is a significant issue with many applications in surveillance, behaviour analysis, and human-computer interaction areas. It has a growing number of uses [17]. There are two classifications of visual tracking methods, deterministic and stochastic tracking. Mean their most familiar representatives are shift and particle filter, respectively [18].

However, particle filtering is the process of combining particles at a single location. A specific point into a single particle, resulting in weight for each particle to indicate the number of particles. It was created by combining various elements. Which eliminates the requirement for exact computations without skewing the results distribution of probabilities. As a result, the cost will be lower. In contrast, to limit the number of samples that must be processed, it is necessary to incur a computational charge that we investigate [19]. The basic architecture of particle filter-based visual object tracking is depicted in Fig. 2.

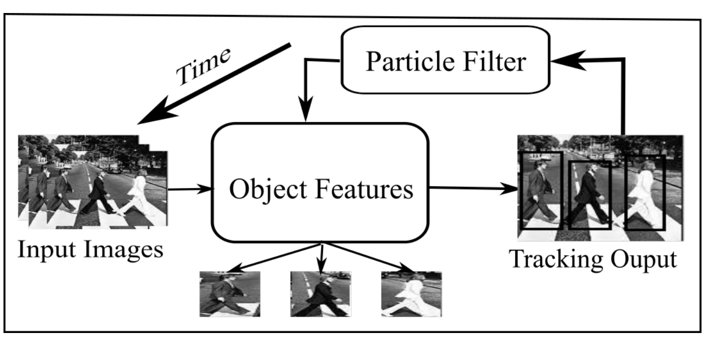

Fig. 2. Block diagram of the particle filter based visual object tracking.

Sequential importance sampling(SIS) is the most critical stage of the PF. At first, a set of particles is created, and then the crucial weights are assigned. Calculated in order to find the state's estimated worth. The majority of the consequences of SIS, after multiple iterations, a large number of particles are ignored, leaving only a small number of particles, possibly even a single particle [20].

SIS, unlike other methods, is not based on the Markov chain. One problem with SIS is that it is far too simple to get to a point where only a few (or one) have non-zero weights and almost all of the particles have weights of zero. These actual weights may differ significantly, leading to an inaccurate estimate. The SIS filter is affected by the so-called degeneracy problem. The SIS method is applicable to non-Bayesian computations as well, like figuring out the probability function in a case of missing data [21].

The following are the different versions of the particle filter [21], [22]:

(a) Local Linearization Particle Filter
(b) Sequential Importance Re-sampling (SIR) Filter
(c) Rejection Particle Filter
(d) Boosted Particle Filter
(e) Rao-Blackwellization
(f) Kernel Smoothing and Regularization
(g) Mixture Kalman Filter
(h) Interacting Multiple Model (IMM) Particle Filters
(i) MCMC Particle Filter
(j) Mixture Particle Filter.
(k) Auxiliary Particle Filter
(l) Unscented Particle Filter

Local Linearisation Particle Filter: The LLPF employs banks of Kalman filters with independent variants to generate credible densities using the most recent measurement.

Sequential Importance Re-sampling Filter: A generalization of particle filtering, SIR called Bootstrap Filter incorporates the re-sampling steps into the sequential importance sampling process.

Bootstrap and jackknife approaches serve as inspiration for sampling importance re-sampling (SIR). Description of a collection of computationally costly procedures built on sampling from observable data, the term "bootstrap technique" is used. The significance distribution is an approximation of the posterior distribution of states given the values from the previous stage, and its accuracy determines the effectiveness of the SIR algorithm. A SIR filter facilitates the examination of importance weights, importance density, substantial modularity, and generality [23].

SIR has the drawback of causing the particle swarm to "impoverish", as the name suggests. When the dynamic model's noise is tiny, many of the particle set's values will have the same value, which is what we mean by the term "the same". The second problem is that a large ensemble size is required to represent much regions in phase space (outliers occur), if the posterior distribution has long tails.

However, important Sampling techniques are used in both SIS and SIR filters. Re-sampling is always performed in the SIR filter (often between two critical sampling stages). In contrast, significance weights are calculated sequentially in the

SSIS filter and only need to be re sampled when necessary. This makes the SIS filter more computationally efficient.

Rejection Particle Filter: When we have a sufficient upper limit on the underlying distribution or density, the rejection particle becomes convenient. The rejection particle filter works better than the SIR filter when the distribution of proposals is preferable. The problem with using a rejection particle filter is that each time step takes a different amount of time to calculate.

Boosted particle Filter: There are two major issues that must be addressed in a traditional particle filter: setting up the particle filter and making sure the importance proposition is set up correctly. The BPF solves both problems by combining them with the AdaBoost detection algorithm [29].

Rao-Blackwellization: Since the process noise is formally zero in pure recursive estimation, the performance of a primary SIR-based particle filter is expected to be sub-optimal. Rao-Blackwellization is one method for increasing SIR efficiency. The fundamental idea behind this filter is to reduce the number of particles required to obtain the same level of accuracy as a standard PF filter.

Kernel Smoothing and Regularization: The problem of insufficient samples was fixed by these filters through the use of a ad hoc method called jittering. To smooth the posterior using a Gaussian kernel, Gaussian noise with a small amount is added to each re-sampled particle at each time step.

Mixture Kalman Filter: The MKF, which simulates a conditional Gaussian linear dynamic model, can be produced by Rao-Blackwellization and marginalization on a particle filter. The MKF represents the target distribution as a random mixture of normal distributions [27]. Primary benefit of MKF is the marginalization operation, which improves productivity.

Interacting Multiple Model Particle Filter: To forecast target behavior, the IMM comprises a range of models and adaptively chooses the models that are best for the current time step. It says that one of M modes best describes how a target behaves when moving with constant velocity, stopped, or accelerating. There is a probability attached to each mode [24].

Markov Chain Monte Carlo Particle Filter: In the MCMC sampling framework, samples are generated by a Markov chain that is ergodic, homogeneous, and reversible, and that has an invariant distribution. A faster rate of convergence than the particle filter is achieved by using this filter. Traditional re-sampling is replaced with MCMC sampling to prevent diversity loss and provide a re-sampling framework appropriate for pipeline processing [26].

Mixture Particle Filter: The MPF idea uses EKF/UKF as an approximation of a Gaussian proposal, and is comparable to the concepts of partitioned and stratified sampling.

Auxiliary Particle Filter: Pitt and Shephard proposed the APF in 1999 to address the tail observation density deficiencies of SIR [25]. As a result, calculating the APF requires more time. The tails of the distribution have low density because of sampling inefficiency and the unreliability of empirical prediction, downsides lack robustness against outliers. For the aforementioned issue, an auxiliary variable was added to the particle filter, resulting in a basic but more versatile and reputable framework with better performance than the SIR filter, although execution is not guaranteed.

Unscented Particle Filter: A particle filter with a UKF significance distribution constitutes the UPF. The proposal distribution in a conventional particle filter, such as CONDENSATION, is transition prior, but UPF was recently proposed to overcome the difficulties of wasting a large number of particles in the low likelihood region [28].

IV. Benchmark Dataset for Visual Object Tracking

A significant number of benchmark datasets have been generated for various visual object tracking applications. Most of them comprise video sequences with short-term (ST) visual object tracking, although long-term (LT) object tracking has been developed in recent years as illustrated in the Table I.

CAVIAR (CAVIAR2003) [39]: It includes two datasets containing several video sequences for various settings, such as persons walking alone or meeting with others. The first dataset contains films from $INRIA$ Labs' entry lobby, whereas the second is from a shopping mall hallway. Walking, browsing, relaxing, slumping or fainting, leaving luggage behind, people/groups walking together and splitting up, and two people arguing are among the scenarios covered in the first set. Each video sequence's ground truth is delivered in XML format and includes information such as bounding box locations and sizes, head and foot positions, and so on. Occlusion, appearance shifting, appearance, and disappearance are all issues addressed in this dataset.

Tracking and Surveillance Performance Evaluation (PETS2009 and PETS2012) [30],[38]: PETS-2009 and PETS-2012 are two of the most recent editions of PETS. PETS2017 has the most recent tracking video sequences, while PETS2012 datasets are identical to PETS2009, mainly aimed at surveillance applications. PETS 2009-S2 provides a dataset for people tracking in three crowd types: sparse, medium, and dense, with L1, L2, and L3 difficulty levels. Walking, running, and multiple flow merging are among the activities covered in the datasets. The goal is to monitor every person in the sequence, with the results being given as a 2D bounding box location for each person. There are difficulties in the dataset, such as occlusion, lighting changes, two people with the same appearance, etc.

Benchmark for online tracking (OTB-13 and OTB-15) [41]: OTB-13 has just 50 video sequences. The current version, OTB-15, is an expansion of OTB-13. The benchmark includes 50 and 100 video sequences, each with features. The datasets take into account eleven different attributes. Lighting, scale, occlusion, deformation, motion blur, fast motion, in-plane rotation, out-of-plane rotation, out-of-view, background clutters, and low resolution are some of them. The tracker's accuracy and location error are the two measures used to evaluate trackers. For assessing and comparing various tracker findings, success plots and precision plots are employed.

LITIV (LITIV) [31]: The dataset consists of people's heads being tracked in various situations (occlusions, many distractors, etc.). Ground facts containing the centers, widths, and heights of tracked object bounding boxes are delivered with video sequences.

Benchmark for Multiple Object Tracking (MOT) [40]: The MOT challenge was initially released in 2015. It comprises annotated datasets, metrics for evaluating tracking methods, and a unified framework for multi-object tracking. MOT15, MOT16, MOT17, MOT20, and many other video sequences are available on the website. The CLEAR metrics(measures used in the classification of events, activities, and relationships workshops) and the collection of track quality measurements are utilized for evaluation [43]. The video sequences of ETH Central, TUD Stadtmitte, and TUD crossing can be found in MOT15.

Visual Object Tracking Challenge (VOT) [42]: The first tracker challenge for ST tracking was VOT2013. Every year since then, a challenge has been held. This paper makes use of VOT2016 [37], VOT2017 [36], and VOT2018 [35] datasets. It evaluates using two metrics. The first is accuracy, which is determined by calculating the overlap ratio between the tracker and ground truth bounding boxes, and the second is robustness, which is determined by tracking failure frequency. These measures have been replaced by the predicted average overlap measure [44] since VOT2015. The current version of VOT2020 includes video sequences for ST and LT tracking as well as an assessment platform.

A UAV Tracking Benchmark and Simulator (UAV123 and UAV20L) [32]: It features video sequences shot from an aerial perspective, with a subset of these sequences dedicated to long−term aerial tracking. Bounding boxes have been added to all sequences and twelve characteristics are used to evaluate trackers.

Single item tracking on a large scale (LaSOT) [34]: LaSOT is a long-term tracking benchmark for large-scale single object tracking. It includes video sequences in which the target vanishes and reappears. Annotations are supplied for each frame in the sequences. Lighting variation, full occlusion, partial occlusion, deformation, motion blur, fast motion, scale variation, camera motion, rotation, background clutter, poor resolution, viewpoint shift, out-of-view, and aspect ratio change are among the 14 qualities assigned to each sequence. It uses three measures for evaluation: accuracy, normalized precision, and success plots [33].

V. Comparison of Particle Filter System for Visual Object Tracking

Object tracking is a critical issue with the expansion of computer vision applications such as video surveillance, human-computer interaction, human behavior analysis, and so on. The following Table II provides a comparison of various algorithms for tracking visual objects using particle filters. Different versions of particle filters are employed with several features to obtain better tracking results.

TABLE I. Benchmark Dataset for Visual Object Tracking in Recent Years

Dataset	Type	Frame Per Seconds	Number of Attributes used for Evaluation	Number of Videos
CAVIAR (2003)	ST	25	–	44
PETS (2009, 2012)	ST	–	–	3(2009), 3(2012)
OTB (2013, 2015)	ST	30	11	50(2013), 100(2015)
LITIV (2014)	ST	15	–	4
MOT (2015, 2016, 2017, 2020)	ST	30(MOT15), 30(MOT16), 30(MOT17) 25(MOT20)	–	22(2015), 14(2016), 42(2017), 8(2020)
VOT (2013-2020)	ST, LT	30	–	16ST(2013), 25ST(2014), 60ST(2015-2017), 60ST & 35 LT(2018), 60ST & 50LT(2019 -2020)
UAV (2016)	ST, LT	30	12	123 ST & 20 LT
LaSOT (2019)	LT	30	14	1400

Note: ST means short-term tracking video, – means not mentioned and LT means long-term tracking video.

VI. Conclusion

This article reviewed particle filter-based approaches for visual object tracking and provided a succinct overview of related subjects. Due to its many practical applications, visual object tracking is one of the most researched computer vision topics. Numerous techniques have been developed for visual object tracking. Particle filter-based visual object tracking has been the subject of extensive research due to its capacity to deal with the complex dynamic environments of real life, random motions, many objects, and non-Gaussian sensor noises. In addition, the convolutional neural network and particle filter have been combined to create the most sophisticated method for visual object tracking. Several characteristics and classifiers that are frequently used with particle filters are provided. It was also found that combining multiple particle algorithms led to successful tracking outcomes and that each method has a unique advantage when considering the different visual object tracking circumstances.

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TABLE II. SUMMARIZING OF VISUAL OBJECT TRACKING USING VARIOUS PF BASED METHODS

SL No.	Paper Title	Year	Contribution	Remarks
1.	"Particle filter-based video object tracking using feature fusion in template partitions." [45]	2023	The research provides a novel approach to feature fusion that aims to improve the target and scene models in order to effectively partition the tracking template and capture the object's local attributes. The proposed strategy combines two features, namely the local binary pattern (LBP) and the mean RGB color features, to account for challenges such as shadows, dynamic background entities, adverse weather conditions, and variations in illumination.	The effectiveness of the suggested feature fusion strategy may exhibit variation depending on the various attributes of the tracked entities and the complex nature of the background scenes. However, the absence of an exhaustive examination of the trade-off between precision and computational efficacy may pose limitations in terms of execution in real-time and efficiency.
2.	"Particle Filter Based on the Harris Hawks Optimization Algorithm for Underwater Visual Tracking." [46]	2023	This study introduced a novel tracking algorithm, Harris-Hawks-optimized particle filters (HHOPF), to address the problem of low tracking accuracy in conventional particle filters caused by sample impoverishment. Using the Harris hawks algorithm, the proposed algorithm generates a nonlinear escape energy that effectively balances the exploration and exploitation processes. Consequently, the computational speed of tracking underwater targets is significantly increased.	The paper lacks a comprehensive analysis of the potential effects of diverse environmental conditions or scenarios on the algorithm's effectiveness. It does not address the difficulties or constraints associated with the use of the Harris hawks optimization technique for underwater visual tracking. In addition, the study lacks an exhaustive assessment of various cutting-edge tracking techniques, which may limit the practical significance of the findings.
3.	"Self-scale estimation of the tracking window merged with an adaptive particle filter tracker." [47]	2023	This research presents a new methodology for single-object tracking that integrates the particle filter algorithm and kernel distribution. This approach enables the tracking window to be updated based on changes in the object's scale, resulting in improved precision in localizing the object within a designated area. The proposed method addresses the difficulty of adapting tracking windows in real-time to account for variations in the object's appearance.	The work lacks a comprehensive examination of the computing complexity associated with the suggested approach. This aspect holds significance for real-time tracking applications that aim to tackle the difficulties of simultaneously tracking several objects.
4.	"A scale adaptive generative target tracking method based on modified particle filter." [48]	2023	This study presents a novel approach to enhance the accuracy and sample diversity of target tracking. The proposed method, named Quantum Particle Swarm Optimization (QPSO) and Adaptive Genetic Algorithm (QAPF), integrates an advanced particle filter (PF) algorithm with the mean shift technique. The objective is to optimize the robustness and intelligence of the traditional PF algorithm across various tracking conditions. By improving the position estimation of particles, the QAPF algorithm aims to enhance the overall performance of target tracking.	This study does not address the computational complexity or resource demands of the QAPF method. Additionally, the comparison of the QAPF algorithm with several state-of-the-art tracking techniques is limited in scope.
5.	"Robust Bayesian particle filter for space object tracking under severe uncertainty." [49]	2022	This paper proposes a particle filtering-based tracking system based on the concept of feature fusion in a complicated real-world environment with shadows, dynamic objects, adverse weather, and changing lighting. The tracking template comprises the local binary pattern (LBP) and the mean RGB color characteristics combined within a probabilistic framework.	Occlusion and concealment issues in dynamic scenes are among the limitations of the proposed system.
6.	"Multi-Feature Single Target Robust Tracking Fused with Particle Filter." [50]	2022	This work presents a credible particle filter with the correlation filtering framework-based multi-feature algorithm for tracking single targets in complex scenes. During feature extraction, depth features and manually extracted target object features are combined to train a tracking filter.	The proposed algorithm's high computational cost for utilizing depth features renders it unsuitable for real-time applications, necessitating additional research to improve its speed.
7.	"Minimax Monte Carlo object tracking." [51]	2022	The authors propose a new particle filter-based approach based on a minimax estimator combined with sequential Monte Carlo filtering for visual object tracking using a minimax strategy.	Only a few algorithms are used to compare performance.
8.	"An object tracking algorithm based on adaptive particle filtering and deep correlation multi-model." [52]	2022	The proposed object tracking algorithm solves the significant number of particles problem by utilizing a deep conventional correlation multi-model on adaptive particle filtering.	The proposed algorithm's performance decreases when the tracking object moves quickly.
9.	"Deep convolutional correlation iterative particle filter for visual tracking." [53]	2022	This paper proposes a novel iterative particle filter-based visual tracking framework based on the combination of a correlation filter and a deep convolutional neural network. In contrast, the iterative particle filter is used to select the correct particles and converge on the target position.	Compared to the other algorithms in the proposed work, the processing rate is lower.
10.	"Occluded object tracking using object-background prototypes and particle filter." [54]	2021	This article introduces an object-background prototypes-based discriminative model to address the shortage of valuable observations and the particle filter's efficient motion. A discriminative model is built using background and object knowledge and attempts to distinguish between the object, background, and any occluded parts of the object.	This algorithm performs well with occluded challenges in complex environments but is limited to other pose changes, illumination, and scale variations settings.
11.	"Multi-object tracking by mutual supervision of CNN and particle filter." [55]	2021	The authors proposed the mutual supervision of the trained CNN detector to identify the target bounding box in a traffic scene and the PF tracker to generate the multi-object tracking trajectory based on this identification.	The proposed algorithm can track rigid targets in controlled environments, like vehicles, but not overall targets like pedestrians.
12.	"Target tracking using a mean-shift occlusion aware particle filter." [56]	2021	This research paper aims to overcome the challenge of occlusion in visual tracking by including the mean-shift approach in a probabilistic filtering framework. This integration allows for a reduced particle set while still effectively maintaining the state probability density function of the model. The proposed approach demonstrates superior performance compared to state-of-the-art tracking algorithms on three benchmark datasets.	The research lacks a comprehensive examination of the computational expenses related to reducing the number of particles for tracking purposes and fails to offer precise quantitative comparisons with methods that employ larger quantities of particles.
13.	"Robust model adaption for color-based particle filter tracking with contextual information." [57]	2021	This study introduces a novel algorithm designed to improve the durability of color-based particle filters. Utilizing environmental data, the proposed algorithm dynamically updates both the scale of the tracker and the reference appearance model. It addresses the challenges posed by abrupt and significant changes in the appearance of the target during object tracking in video sequences.	The work lacks a comparative analysis of the proposed algorithm to a variety of cutting-edge trackers to provide a greater understanding of the algorithm's strengths and weaknesses. Further analysis that does not fully reflect the complexity and variability of real-world tracking scenarios could shed light on the robustness and generalizability of the proposed methodology.

SL No.	Paper Title	Year	Contribution	Remarks
14.	"Visual Vehicle Tracking via Deep Learning and Particle Filter." [58]	2021	The research presented a novel and efficient method for tracking multiple vehicles by combining the particle filter technique with the deep learning approach called You Only Look Once (YOLO). The authors perform an evaluation of a pragmatic tracking approach that employs the particle filter and the Bhattacharyya kernel to provide a feasible resolution for real-time tracking of multiple vehicles in different situations.	The study does not include a comprehensive examination of the computational complexity and lacks a comparison of the proposed approach with other well-recognized vehicle tracking techniques. As a result, the authors failed to address shortcomings or difficulties associated with using the YOLO detector for vehicle detection, such as how well it functions in different lighting conditions or in occlusion-prone situations.
15.	"Tracking and grasping of moving target based on accelerated geometric particle filter on the colored image." [59]	2021	This study presents a novel approach for tracking and retrieval of objects in unpredictable motion by employing a geometric particle filter tracker. The reduction in computational expenditure is accomplished by employing edge detection and morphological dilation methodologies. Furthermore, the tracking algorithm integrates HSV image features rather than grayscale image features, thereby improving its capacity to adjust to changes in illumination conditions.	A novel method for tracking and grasping moving objects is presented in this paper. Nevertheless, it does not analyze the handling of complex background scenarios or object occlusion, which are common challenges in tracking and grasping tasks in the real world.
16.	"A genetic optimization re-sampling based particle filtering algorithm for indoor target tracking." [60]	2021	This study presents a novel resampling technique intended to address the issue of particle erosion commonly observed with conventional resampling methods. The distribution of resampled particles is optimized by employing five operators, namely selection, roughening, classification, crossover, and mutation. These operators are employed to decrease particle depletion and improve particle positioning precision.	The study focuses primarily on indoor target tracking via wireless sensor networks. Uncertain is the extent to which the proposed algorithm would function effectively in outdoor settings or with various sensor types.
17.	"Particle filter and entropy-based measure for tracking of video objects." [61]	2021	The authors present a novel approach based on the particle filter for tracking objects in outdoor and indoor video sequences, using an entropy-based time motion searching model for selecting the particles to detect objects.	The proposed approach includes a performance comparison.
18.	"Deep convolutional likelihood particle filter for visual tracking." [62]	2021	This paper proposes a novel particle filter for visual tracking based on convolutional-correlation particle filters that estimate likelihood distributions from correlation response maps.	The weakness of the proposed method is that it does not fully explain all parts of the algorithm.
19.	"Infrared target tracking based on improved particle filtering." [63]	2021	To solve the infrared image particle degradation problem, this paper presents a combination of genetic algorithms and extended Kalman filter-based particle filter tracking with improved performance for infrared target tracking.	Utilizing a genetic algorithm and an extended Kalman filter increases the computational complexity of the proposed particle filter.
20.	"Visual object tracking via iterative ant particle filtering." [64]	2020	The author provides a particle filter-based tracking method with discriminative model-based object background prototypes for identifying objects and occluded portions of objects. The discriminative model uses prior knowledge of object and background classes to differentiate between three categories: object, background, and occluded object parts.	This method overlooked other relevant variables such as lighting variance, pose change, and scale change.
21.	"Tracking objects based on multiple particle filters for multipart combined moving directions information." [65]	2020	This study introduces the mutual supervision of the PF tracker and CNN detector to create the multi-object tracking trajectory, whereas a trained CNN is used to identify the bounding box of the detected target in a traffic scenario.	The main limitation of this study occurs under controlled conditions, such as tracking people from a traffic scene.
22.	"Occlusion robust object tracking with modified particle filter framework." [66]	2020	The authors present a particle filter that combines the mean-shift approach into a probabilistic filtering framework while using fewer particles to maintain many modes' state probability density function. The reference target and candidate location correlation coefficient, however, detect occlusion.	The proposed MSOAPF technique includes occlusion and fast motion challenges but fails in extensive situations.
23.	"A hybrid algorithm based on particle filter and genetic algorithm for target tracking." [67]	2020	This paper proposes a crew search optimization-based robust particle filter re-sampling method for overcoming low-performing particles identified as outliers by incorporating multi-cue extracted for each evaluated particle.	This approach is computationally demanding as an outlier detection is used to categorize unimportant particles.
24.	"Robust object tracking with crow search optimized multi-cue particle filter." [68]	2020	In this study, an observer marks an object at the beginning of a video sequence to reduce the image size by selecting particles with the highest weights to evolve a genetic algorithm known as the Reduced Particle Filter Genetic Algorithm during the re-sampling phase of the particle filter.	This algorithm's performance is not calculated and compared conclusively with other state-of-the-art algorithms.
25.	"Intelligent visual object tracking with particle filter based on Modified Grey Wolf Optimizer." [69]	2019	In this paper, the author proposes a visual object tracking system based on the Modified Grey Wolf Optimizer (MGWO) to address the issue of many particles in the particle filter (PF). Before re-sampling, the PF particles were optimized using a new variant of Grey Wolf Optimizer known as Modified Grey Wolf Optimizer (MGWO).	The proposed MGWO-based PF is not fully explained and is only compared to a few algorithms.
26.	"Multiple pedestrian tracking by combining particle filter and network flow model." [70]	2019	This paper suggested a novel particle filter tracking system for multiple pedestrians based on network flow models. To compensate for the problem of long-term occlusion, the proposed model combines local and global data association strategies.	The weakness of the proposed method is that both the computational complexity and the number of particles increase as the number of objects increases.
27.	"Multi-feature fusion in particle filter framework for visual tracking." [71]	2019	The authors applied the color distribution, and KAZE features with the particle filter (PF) to track a target in a video sequence of complex environments. The proposed multi-feature fusion-based PF utilized the Bhattacharya coefficient for the color distribution model as a similarity metric. At the same time, KAZE features utilized the Nearest Neighbor Distance ratio for matching feature points.	In PF experiments, only color and KAZE characteristics are employed. A set of features that accurately represents the target in one environment may not do so in another.
28.	"Particle filter re-detection for visual tracking via correlation filters." [72]	2019	This paper proposes a novel particle filter re-detection tracker with a correlation filters framework (CFPFT) to solve the problem of accurate object localization.	Long-term occlusions may still cause the tracking method to fail, so a strategy that re-detects the target and reuses the correlation filter tracker was to be implemented in real-world applications.
29.	"Robust object tracking via integration of particle filtering with deep detection." [73]	2019	This paper proposes a video object tracker with variable-rate color particle filtering that incorporates two innovations. First, a deep region proposal network was used to select the bounding box based on the dynamic prediction of particle filtering and a fusion integrating the particle filter and a deep object detector to enhance object tracking accuracy.	Implementation of the proposed method is slower than the conventional particle filter method, with only minor improvements.

SL No.	Paper Title	Year	Contribution	Remarks
30.	“Visual tracking based on adaptive interacting multiple model particle filter by fusing multiples cues.” [74]	2018	This paper presents a robust tracking system based on the fusion of a particle filter (PF) with interacting multiple models (IMM) to overcome various severe challenges, such as camera motion, fast motion, background clutter, or target appearance changes.	The performance of the proposed algorithm decreases while the tracked object moves quickly.
31.	“Chaotic particle filter for visual object tracking.” [75]	2018	The authors introduced a chaotic particle filter (PF) based on global motion to enhance the performance of PFs. In two steps of chaos theory, estimation of the object’s movement is used to identify its position over frames, followed by the color-based particle filter technique to find the object in the local region.	The chaotic PF method outperforms the conventional PF method and occasionally the tracking by detection techniques, but only color features are used in all studies.
32.	“Robust object tracking via part-based correlation particle filter.” [76]	2018	This paper proposes a part-based correlation particle filter method for reliable visual tracking. In a particle filter architecture, correlation filters manage target parts and accurately represent the target’s appearance by employing overlapping local parts of varying sizes and locations.	The main downside of the method is that it works better when tracking nonrigid objects with changing appearances, but it disregards other relevant difficulties.
33.	“A box particle filter method for tracking multiple extended objects.” [77]	2018	This paper proposed a box particle filter-based extended multiple object tracking technique to address the challenging problem of multiple object tracking caused by data association. This research also highlights how interval-based techniques can manage data association concerns effectively while minimizing computational complexity.	The validation of the proposed approach is limited to laser rangefinder sensor data in real time and needs to be expanded and validated in more generic application settings.
34.	“Multi-task correlation particle filter for robust object tracking.” [78]	2017	This study presented a particle filter based on a multitask correlation named MCPF for effective visual object tracking. In contrast, correlation filters jointly learn the interdependencies across numerous features from the multitask correlation filter (MCF).	Using a multitask correlation filter increases the computational cost of the proposed MCPF.
35.	“Particle Filter Object Tracking Based on Color Histogram and Gabor Filter Magnitude.” [79]	2017	The authors present a novel particle filter-based tracking method that uses the combination of Gabor filter features and the color histogram of the detected object, obtained by background subtraction, to determine the likelihood of the observation and a state space model based on the Box-Muller transformation.	The proposed method’s main drawback is that the number of particles increases when the object’s color histogram increases, causing computational complexity.
36.	“Correlation particle filter for visual tracking.” [80]	2017	The authors propose a robust correlation particle filter (CPF) for visual tracking by combining the strengths of a correlation filter and a particle filter.	The performance metric of the algorithm is not computed comprehensively.
37.	“Deep convolutional particle filter for visual tracking.” [81]	2017	The integration of a particle filter and deep CNN has been proposed in which the particle filter predicts the target position using motion mode at each frame, and the HCFT-CNN adjusts the target position using the surrounding particles of the anticipated position. Finally, the CNN correlation map was used to calculate the current frame’s particle weight and target position.	The presented paper contains no accurate experimental results.
38.	“Top-down visual attention integrated particle filter for robust object tracking.” [82]	2016	This study blends frequency analysis into a particle filter-based computational of top-down visual attention to address the challenges of rapid motion and long-term obstruction.	The tracker’s performance suffers slightly if the object appearance changes and if descriptors calculated directly from feature maps are used instead of color histograms, making it more coherent and faster.
39.	“Adaptive Cell-Size HoG Based Object Tracking with Particle Filter.” [83]	2016	The authors proposed an Adaptive cell-size HoG (acHoG)-based Particle Filter Tracking (PFT) algorithm to handle the repeating feature extraction problem by applying Adaptive cell size to HoG.	The main drawback of these approaches is that they reduce tracker performance due to failure detection.
40.	“Object-tracking based on particle filter using particle swarm optimization with density estimation.” [84]	2016	The authors analyze the problems of particle filter tracking degeneracy and impoverishment degradation in the Bayesian particle filter tracking framework. Particle Swarm Optimization (PSO) is employed as a sampling mechanism to address these two issues.	The proposed solution did not handle other critical challenges such as backdrop adaption, scene tracking in a cluttered environment, and object interactions.
41.	“Real-time and model-free object tracking using particle filter with joint color-spatial descriptor.” [85]	2015	The authors incorporate the Joint Color-Spatial Descriptor (JCSD) and particle filtering to develop a multiple model-free object tracking technique that evaluates the hypothesis step within a particle filtering framework.	However, the method’s accuracy decreases with low computational power and must be implemented with GPU for high accuracy and real-time applications.
42.	“Single object tracking via a robust combination of particle filter and sparse representation.” [86]	2015	This author presented a particle filter-based tracking system that uses a particle filter and reversed sparse representation (RC-PFRSR) comprehensive combination to reduce drifting and increase tracking robustness.	In this study, the proposed system tracks only a single visual object and not multiple visual objects.
43.	“Particle filter with occlusion handling for visual tracking.” [87]	2015	The authors proposed a particle filter system with a patch-based appearance model for occlusion handling, which includes two main components: color and motion vector, to address the challenge of visual tracking with three critical components including feature extraction, particle weighting, and occlusion handling.	The key drawback of the strategy is that it only worked for occluded environments as opposed to other constraints in visual object tracking.
44.	“Intelligent video target tracking using an evolutionary particle filter based upon improved cuckoo search.” [88]	2014	This paper aims to incorporate an evolutionary particle filter with an improved cuckoo search algorithm to overcome the sample impoverishment problem of a generic particle filter in real-time video object tracking. Regarding tracking performance, the proposed algorithm outperforms the PSO particle filter and generic particle filter based on an improved cuckoo particle filter.	The proposed system is adequate for tracking a single object, not multiple objects, or in ambiguous or uncertain environments. Furthermore, this tracking framework necessitates additional cues to handle dynamic object shapes.
45.	“Using local saliency for object tracking with particle filters.” [89]	2014	Instead of employing the saliency map of the entire image, the authors proposed a tracking algorithm that estimates the saliency map by extracting salient regions based on visual attention from the particle areas and the target area of each particle.	The proposed algorithm resolves particle filter divergence for targets with similar characteristics. However, tracking errors are inevitable when target and background colors are similar.
46.	“Abrupt motion tracking using a visual saliency embedded particle filter.” [90]	2014	This article illustrates how to solve the problem of abrupt motion by combining a particle filter tracking system with an improved visual saliency model. In addition, it is possible to recover a lost tracking object by detecting its region in salient regions.	In this proposed work, many tracking aspects under challenging conditions, such as when the target object is visually similar to the background or when its appearance abruptly changes, are not considered.

SL No.	Paper Title	Year	Contribution	Remarks
47.	"Object tracking from image sequences using adaptive models in the fuzzy particle filter." [91]	2013	This paper addresses issues caused by unexpected events. In the proposed work, a fuzzy particle filter's process and observation noises are considered fuzzy variables. The fuzzy particle filter is equipped with two adaptive models that enhance tracking performance: adaptive AR and appearance mixture. The adaptive AR calculation is adopted as the state transition model, and recursive AR determines the optimal parameters over time to enhance state prediction. Additionally, the observation model, the adaptive appearance mixture model, consists of three Gaussian components (W, S, and E).	This method did not consider object illumination or occlusion when tracking multiple objects.
48.	"A combined Color-Correlation Visual Model for Object Tracking using Particle Filters." [92]	2013	The proposed work utilizes a particle filter to track semi-rigid video sequence objects. In addition, the MOSSE correlation filter and color histogram combination create a robust feature descriptor of the object that outperforms for tracking fast-moving objects in a complex environment in real-time applications with a small number of particles.	This paper's limitation is that the required computing power for the tracking system depends not only on the size of the patches but also on the number of particles. In addition, the system must investigate sampling inefficiencies and maximize particle utilization.
49.	"Efficient visual tracking using particle filter with incremental likelihood calculation." [93]	2012	This paper proposes an improved real-time particle filter in which the weight of each particle is computed using incremental likelihood. However, the proposed particle filter-based tracking method performs surprisingly well on hardware platforms with limited resources.	The proposed tracking method's effectiveness diminishes as the tracked object's speed increases. Therefore, it is only effective when an object moves at a reasonable speed; this is the trade-off between the proposed approach's accuracy and the object's speed.
50.	"A compact association of particle filtering and kernel-based object tracking." [94]	2012	The main goal of this paper is to combine kernel-based object tracking (KBOT) and particle filtering (PF) to develop a more reliable visual tracking method (PF). In addition, the question of what types of particles are appropriate for using KBOT to refine their position states for more accuracy is also addressed, and a two-stage solution is proposed.	There are still some issues that demand more research. The disadvantage of the proposed algorithm's use of color histograms as object descriptors for a fair comparison is that it is unsuitable for dealing with varying lighting conditions.
51.	"Hierarchical Kalman-particle filter with adaptation to motion changes for object tracking." [95]	2011	The authors examined the combination of the particle filter and subspace representation and successfully applied it to tracking algorithms, such as the Eigen-tracking technique. Their combination has shown improved performance in terms of accuracy and robustness despite requiring a relatively small number of particles.	Although the proposed method works with greater accuracy and precision, it is computationally expensive. Moreover, in the proposed technique, the particle filter handles only nonlinear motion locally, while the Kalman filter deals with linear motion globally.
52.	"Robust visual object tracking using multi-mode anisotropic mean shift and particle filters." [96]	2011	This study presents a novel tracking technique based on multi-mode anisotropic mean shift and particle filters. The method performs online learning of reference objects, is more resistant to objects' dynamic shape and appearance, and requires a small number of particles.	The proposed system necessarily requires accelerated computation and empirical parameter selection.

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