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Research Article

Adaptive Object Tracking System Using Swarm Intelligence and Meta Learning Optimization

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ABSTRACT

The core function of computer vision research is object tracking but problems with illumination changes and object obscuration and sensor noise and sudden object motion remain obstacles to reach optimal tracking results. A novel dual-object tracking system developed this study merges Kanade-Lucas-Tomasi (KLT) optical flow tracking and Particle Swarm Optimization (PSO)- based swarm intelligence tracking with meta-learning to boost tracking accuracy and adaptability. This system integrates KLT for tracking target dominant points across video frames with PSO to concurrently track boundary information which produces strong object localization results in dynamic conditions. The system benefits from meta-learning because it helps track procedures by establishing universal knowledge across different scenarios while learning new tasks from limited training data. The experimental testing demonstrates how the proposed system achieves superior performance over current tracking methods in terms of both precision and operation speed and stability. The system demonstrates effective performance when tracking short and long videos under static and dynamic background conditions while overcoming deep learning tracking limitations. This study contributes a cost-effective, scalable, and adaptive tracking framework, suitable for applications such as autonomous navigation, surveillance, and human activity recognition, paving the way for future advancements in intelligent object-tracking systems.

Keywords: Particle swarm optimization, Dual tracking, Meta learning, Kanade-Lucas-Tomasi (KLT).

INTRODUCTION

Object Tracking allows a camera to track moving objects as long as they are within its view range under Variable Background and Static Background conditions. Time-based object detection combined with tracking represents a significant technical obstacle for automatic surveillance systems along with traffic monitoring and vehicle navigation applications. Object tracking becomes significantly hard and complicated in situations where background conditions undergo frequent dynamic modifications because of camera movement together with object speed variations and changes in light conditions

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along with noise disturbances and occlusion situations. The algorithms implementing tracking need to demonstrate robust performance in conjunction with flexible capabilities and adaptable strategies for such unpredictable conditions. The system needs to perform tracking in real time. This system has been operational for multiple decades. Various tracking methods have appeared in research space demonstrating different levels of accuracy and performance (Babenko et al. 2010) (Grabner et al, 2008). Multiple challenging problems persist in tracking because of the causes explained before. We implement dual tracking through optical flow along with swarm intelligence that uses meta-learning to achieve robustness in the face of mentioned challenges.

Meta-learning (Liu et al., 2025) is an advanced paradigm in machine learning that focuses on designing algorithms capable of improving their learning processes over time. Unlike traditional models that learn a specific task, meta-learning systems operate at a higher level by learning how to optimize task-specific models. Object detection involves detecting distinct items within an image and localizing them using a bounding box. Optical flow represents the pattern items. The motion information obtained from optical flow proves useful for researchers who conduct moving object detection and tracking (Schwarz et al., 2012) (Shin et al., 2005). Several optical flow methods exist today which include Lucas—the Kanade method (Tomasi & Takeo, 1991), Horn-Schunck method (Horn, 1968), Buxton-Buxton method, Black-Jepson method among others. Of all the available optical flow approaches Horn- Schunck and Lucas-Kanade stand out as the methods most commonly used. These detection methods demonstrate unique benefits together with individual drawbacks. The researchers at (Shin et al. 2005) introduced object tracking under the non-prior training active feature model through a three-step process starting with object localization and followed by spatiotemporal based correction modeling then applying the NPT-AFM framework.

Meta-learning is employed to enhance the adaptability of the tracking algorithm by enabling the system to learn from a collection of tasks and improve its performance in few-shot scenarios. By refining the model on tasks with minimal data, meta-learning ensures that the tracking algorithm remains effective in dynamically changing environments. Unlike conventional methods that primarily focus on classification, this work integrates meta-learning to address challenges in object tracking, making the system more robust and versatile in real-time applications. Figure 1 provides examples of meta-learning applied to few-shot object detection.

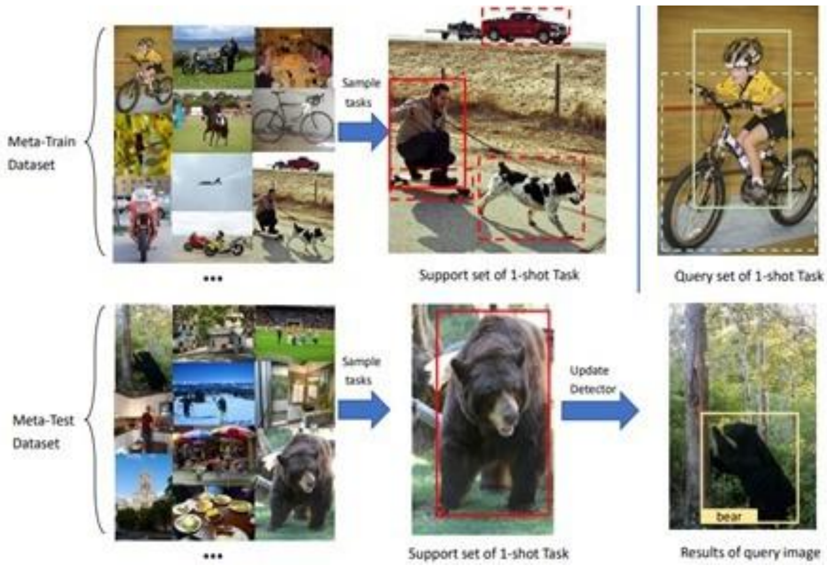

Figure 1. Example of a few short object detection with meta learning

The KLT method serves as a popular selection for object tracking applications as demonstrated by (Stiefelhagen et al. 2007) when handling multiple-point tracking in parallel environments. The video object segmentation process followed by optical flow application to track segments was implemented by (Chen et al, 2011). The authors at (Cui et al, 2013) developed a probabilistic tracking system that merged low-dimensional with high-dimensional tracking techniques. Tsutsui et al., 2001 developed an optical flow-based tracking solution which used multiple cameras instead of a single camera. This method determined object positions during occlusion using different camera perspectives. The research community engaged in two works of 2012 first (Liu et al., 2012) developed a tracking technique merging lower and higher dimensional information then (Brox et al., 2006) presented a 3D pose-tracking system through optical flow with contour and flow-based boundary techniques. The system of Aslani et al. (2013) merged both optical flow computation with image processing methods to obtain pixel location data from object movement between sequential frames for complete tracking control. The method used optical flow to create motion vectors that performed frame-to-frame object position prediction based on (Kale et al., 2015). The broad utilization of optical flow in object detection and tracking continues to struggle with obtaining reliable comprehensive data streams that constitutes an unresolved problem for tracking objects (Husseini, 2017).

The incorporation of meta-learning brings a revolutionary solution for dealing with the identified obstacles. The main goal of meta-learning involves creating tracking models that learn new tasks efficiently using limited data thus making them suitable for changes in environmental conditions including object blocking and lighting adjustments. The research by Wu et al. (2013) presented an evaluation for object tracking that reported metrics from powerful methods including ASLA with its sparse reconstruction system and BSBT applying supervised and semi-supervised recognition and tracking approaches. The tracking system achieves better scenario generalization using meta-learning technology which dynamically readjusts its parameters to enhance processes related to detection segmentation and tracking.

The adaptive capabilities of meta-learning could enhance both probabilistic tracking based on color (CPF) along with the circulant structure of tracking-by-detection with kernels (CSK). Meta-learning allows training across diverse tracking tasks and scenarios which strengthens both the robustness and efficiency of these algorithms for developing real-time adaptive object-tracking systems aimed at resolving long-standing field challenges (Kaihua et al, 2012).

Researchers dedicated extensive attention to bio-inspired tracking tools throughout the past twenty years (Sevilla-Lara et al., 2012). The three methods ACO, PSO and GA gained popularity because of their fast convergence abilities combined with efficient and robust performance.

Research conducted before demonstrated the effectiveness of PSO in tracking problems according to Richards et al (2004). Particle Swarm Optimization enables (Zheng et al., 2008) to search optimal matchings within high-dimensional space features where a pre-defined classifier set detects Haar-Like features. The temporal continuity measurement between two consecutive frames determines swarm particle flights for tracking according to (Li et al, 2008). PSO calculates tracking success by measuring template and object movement differences. The approach proposed in this thesis receives evaluation against the Multiple object tracking using PSO technique (Hsu et al, 2012). The process starts with establishing a grey-level histogram feature model after which PSO particles receive their distribution based on the chosen target object fitness function. The GPU-Accelerated PSO method demonstrated by Rymut et al. (2015) shows how real-time multi-view human body tracking operates by converting 3D human models into their corresponding particle poses which get rasterized in all particle planes.

The present work introduces dual tracking as the main innovation due to the absence of this approach during the previous decades of object tracking research. The proposed dual tracking system demonstrates exceptional reliability when used to monitor short video segments under static backgrounds and variable conditions and also for tracking objects during lengthy video monitoring under static backgrounds with variable conditions. Observations from Simpson (2015) along with our critical assessment and our recent VGGNet experiments show that DNNs represent adult intelligence through accumulated knowledge applied to specific knowledge domains although they operate poorly within novel situations. The authors argue that DNN-based systems should integrate fluid intelligence capabilities with working memory functionality because it allows them to solve abstract problems and novel challenges within unknown environments (Schneider et al., 2012). Such challenging issues together with various other proposals (Gray et al., 2003) need a complete review process to draw final conclusions. An independent work must handle these matters separately from the main discussion.

Our proposed tracking method combines KLT and PSO tracking systems under a dual-tracking optimization that incorporates meta-learning improvements. The innovative algorithm brings effective solutions to complex tracking problems where it outperforms conventional methods. The application of meta-learning removes the requirement for extensive re-training and pre-trained model dependence when tracking previously unseen objects. The real-time calculation of tracking dominant points or boundaries through dynamic process adaptation makes meta-learning possible for achieving seamless tracking in unknown environments.

This tracking framework featuring KLT and PSO integration under meta-learning supervision produces an intelligent system that ensures high accuracy in background conditions that change or stay static. Through their combined functionality the dual trackers form two elements that enhance each other for an overall system which combines robustness and affordability with exceptional performance in situations where DNN-based tracking algorithms typically fail. The proposed dual-tracking algorithm successfully tracks objects within diverse lengths of challenging video sequences. The system can calculate new dominant points for target objects in real-time without needing complete training from scratch just like standard DNN-based tracking methods require.

The proposed method makes use of KLT tracking technology to track dominant points of target objects throughout all video frames with PSO tracking providing boundary monitoring from frame two until the termination. The target object boundary tracking process commences at the second frame through a PSO (Particle Swarm Optimization) tracker based on swarm intelligence. The optimization system of meta-learning controls track interaction by adapting to environmental changes that include variations in illumination and noise as well as occlusion elements. The algorithm displays dependable operation while adapting to static or variable background conditions thanks to its flexible system design that results in successful application in complex tracking solutions. The research develops a dual-tracking algorithm which unites the Kanade-Lucas-Tomasi (KLT) tracker together with the PSO-based tracker and the addition of meta-learning principles for object-tracking tasks.

The paper presents a tracking framework which combines KLT tracker with PSO-based tracker to obtain efficient results through their respective abilities for short and long sequences. A dynamic mechanism based on meta-learning principles operates in the framework to improve tracking algorithm performance through the adaptive framework structure which circumvents time-consuming retraining procedures over different environmental conditions.

This paper can achieve a balance between computational efficiency and tracking accuracy, making the method suitable for real-time applications in both static and dynamic backgrounds. Detection methods help minimize alignment hazards yet knowledge gaps alongside evaluation and comparison issues persist. Standard is necessary to simplify tunnel engineering plan optimization and decision-making processes.

Features of Detection and Tracking

There are no two leaves in the world that are identical; each has its distinct qualities. When tracking an object, the selection of suitable characteristics may significantly alleviate the computational burden (Wolf, 2014) (Yang & Ying, 2005).

While several tracking algorithms use a mix of various aspects, a comprehensive understanding of each feature is crucial for tracking in computer vision. Presented below are a few prevalent characteristics.

A. Color

This aspect of computer vision is often used for histogram-based appearance representations. Furthermore, it is among the most often used functionalities for monitoring (Yoon et al., 2012). The characteristic of color is often represented by the RGB color space, including red, green, and blue. Utilizing color as a characteristic for tracking presents a significant issue since the color feature is readily affected by variations in light.

B. Histogram

HOG (Walk et al., 2010) serves as a widely employed characteristic for human body detection systems along with establishing itself as a dominant feature. Sufficient in-variance against geometric distortion and optical deformation exists within the HOG model through its operation at the local grid unit of pictures. Inside the sample space and with fine orientation sampling and robust local optical normalization conditions in place the human detection outcomes remain unaffected when the human body stands upright despite minimal body movements thus explaining why HOG features are widely used in human detection.

C. Edges

Edge detection is used to discern variations in picture brightness that delineate object boundaries. It differs from color features because of its less sensitivity to variations in light.

D. Optical Flow

The motion-based segmentation and tracking field regularly utilizes optical flow as one of its main features (Li et al, 2014; Dalal &Bill, 2005). A dense field of displacement vectors delineates the translation of each pixel inside an area. The brightness constraint functions as a calculation method to determine optical flow while assuming pixel brightness stays constant from one frame to another. New technological developments have given rise to multiple important algorithms for dense optical flow estimation including the Horn-Schunck Algorithm (Lepetit et al, 2005) (Mokri et al, 2009).

A structured breakdown follows: Section 2 provides an extensive review and discussion of existing object-tracking techniques which ultimately leads to supporting the reason for implementing the new proposed method. The section 3 describes the dual tracking framework through KLT and PSO and meta-learning integration while providing details about system configuration involving datasets. The proposed method achieves evaluation in this section 4 alongside state-of-the-art techniques along with discussion-based results. This work concludes through a summary of findings coupled with contribution highlights and proposed research paths in Section 5.

LITERATURE REVIEW

The research by Liu et al. (2025) developed a few-shot bearing fault diagnosis approach which uses semi-supervised meta-learning alongside a simplified graph convolutional neural network (semi-meta-sgc). The adjustment of spectrum samples into nodes allows KNN to build a network structure which transforms defect classification into structured node classification. Meta-learning and graph convolutional neural networks together with semi-supervised learning enable the development of a node classification system which achieves high accuracy through restricted training sample input for bearing defect recognition across diverse operational conditions. The proposed method achieves final validation through executing four test scenarios alongside alternative method comparison evaluations. The examining data demonstrates that the proposed method outperforms other techniques in recognition accuracy alongside stronger generalization abilities.

The researchers at Wang et al. (2025) established a few-shot defect diagnostic system through their combination of multi-scale perception multi-level feature fusion image quadrant entropy

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(MPMF-FIQE). Transient signals transformed through Gramian angle summation field (GASF) produce pictorial outputs that maintain complex mechanical state information. The fusion image quadrant entropy method combines non-linear dynamic features from these feature maps to generate the mechanical MPMFFIQE set of features.

Experimental case studies validate that MPMFFIQE achieves accuracy gains reaching 12.90% above six alternative feature selection approaches. A single training sample per state enables the proposed model to reach accuracy rates above 98.10% and this surpasses the six current models by 27.48%. The created model demonstrates its capability to detect industrial mechanical problems while maintaining accuracy levels using minimal training example requirements. The model shows excellent universal applicability to different mechanical devices which makes it highly functional for practical purposes.

The authors of (Lateef et al., 2024) presented a method to increase BSO ontology alignment capabilities. The SA-BSO provides a new solution to handle memory allocation alongside algorithm investigation along with exploitation execution. The SA-BSO algorithm promotes effective sensor ontology matching through swarm inter-generation communication methods. The research conducted tests the effectiveness of SA-BSO through three pairs of actual sensor ontologies combined with the Conference track. (Zhang et al., 2024) endowing a deep model with the capability for few-shot learning (FSL) is a fundamental problem in artificial intelligence. Gradient-based meta-learning proficiently tackles the difficulty by acquiring the ability to learn new tasks. The central concept involves training a deep model using bi-level optimization, whereby the outer loop develops a common gradient descent algorithm (termed meta- optimizer), while the inner loop utilizes this method to refine a task-specific base learner with few instances. Despite the greater effectiveness of these approaches in few-shot learning (FSL), the outer-loop procedure necessitates the computation of second-order derivatives along the inner-loop trajectory, resulting in significant memory demands and the potential for vanishing gradients. Drawing from contemporary diffusion models, we observe that the inner-loop gradient descent procedure may be seen as a reversal process (i.e., denoising) of diffusion, whereby the objective of de- noising is the weights of the base learner rather than the original data. Consequently, they suggested conceptualizing the gradient descent algorithm as a diffusion model and introducing a novel conditional diffusion-based meta- learning framework, termed MetaDiff, which adeptly simulates the optimization process of base learner weights transitioning from Gaussian initialization to target weights in a denoising fashion. Due to the training efficiency of diffusion models, our MetaDiff does not need differentiation across the inner-loop route, hence significantly reducing memory loads and mitigating the danger of disappearing gradients to enhance few-shot learning (FSL). Experimental findings indicate that our MetaDiff surpasses the leading gradient-based meta- learning approaches in few-shot learning challenges.

The combination of adaptive gain control algorithm together with flocking SWARM algorithm using adversarial agents enabled a communication-less system to operate at full functionality and speed according to (Tianbo et al., 2023). The research traces the complete cognitive structure of this biological swarm intelligence (Chao et al., 2025) which starts at inception and ends with completion (Flocking algorithm). The system demonstrates a high level of reliability through diverse operations. The system enhances group prediction through neighbors by implementing adaptive gain control and a partial Kalman filter. The SWARM drone's integrated camera can activate the Object Recognition visual technique after the system achieves stability. The system proceeds from simulation to actual operational level. According to Pazho et al. (2023) precise and real-time intelligent surveillance requires immediate attention because vision-based artificial intelligence evolved and Internet of Things-connected cameras expanded and society demanded rapid equitable security systems. The research developed Ancilia as a fully integrated surveillance system which combines scalability and intelligence and was designed specifically for the Artificial Intelligence of Things (AIoT). Ancilla unites modern artificial intelligence technology with real-time functional surveillance through systems which handle ethical obligations when running high-level cognitive operations in real-time. Ancilia ventures into transforming surveillance platforms with powerful and just security solutions that achieve effective protection while maintaining privacy safeguards for individuals.

The combination of unmanned aerial vehicle technology with swarm intelligence enables the standardized development of hundreds of small UAVs into effective military swarms for executing complex combat operations through ad-hoc networks according to Wang et al. (2022), thus creating major defense problems for low-altitude airspace operations. Security at low-altitudes depends on optical tracking systems to identify UAV swarm approaches to allow development of countermeasures for UAV protection. The UAVSwarm dataset contains labeled images from thirteen movie sequences which reveal nineteen drone types across twelve thousand nine hundred ninety-eight pictures while each sequence displays drone numbers from three to twenty-three. The study implements two complicated depth detection models known as Faster R-CNN and YOLOX as benchmark standards. The investigative performance demonstrates that the dataset consists of availability and consistency and universality elements. The UAVSwarm dataset serves practical purposes for different UAV detection systems and UAV swarm multi-object tracking evaluation frameworks.

According to Alrowais et al. (2022) object detection functions as a computer vision method that recognizes semantic objects from their particular class in digital images and videos. Object detection serves as a common application for crowd density analysis in practical use. Crowd density classification models work better with convolutional neural network (CNN) models because non-uniform density and occlusion and inter-scene and intra-scene variations create obstacles in this process. The MDTL-ICDDC method recommends an approach to improve video surveillance system efficiency when detecting and classifying crowd density levels. The MDTL-ICDDC model employs a Salp Swarm Algorithm (SSA) as its hyperparameter optimization method together with NASNetLarge model which extracts features. The MDTL-ICDDC system delivered better performance than each of Gabor, BoW-SRP, Bow-LBP and GLCM-SVM models alongside VGGNet and GoogleNet.

(Usmani et al., 2021) presented a deep learning framework for human action recognition to address the limitations of existing state-of-the-art approaches. Each frame of the action sequences is analyzed for spatial aspects to obtain appearance-based and structural information. Our methodology enables tracking stability and strengthens the tracking process robustness which reaches an accuracy of 97.09%.

(Alqaralleh et al., 2020) presented a novel Reliable Multi-Object Tracking Model using Deep Learning (DL) and Energy Efficient Wireless Multimedia Sensor Networks (WMSN). The identification of cluster heads (CHs) as the first step uses fuzzy logic for reaching energy efficient goals. Researchers then created RNN-T which stands for Recurrent Neural Network with tumbling effect as their tracking technique for implementing in the second phase. The proposed RNN-T model operates on sensor nodes but the cluster heads employ the tracking algorithm for animal observation. Analysis takes place on the cloud server after tracking findings are transferred there. An experimental analysis with genuine animal video data determines the effectiveness of the proposed approach. The RNN-T model demonstrates superior performance than competing techniques according to the research results. (Benabderrahmane et al., 2017) introduced a real-time object recognition and tracking system using Adaboost classification, whereby a robust classifier is constructed via the iterative amalgamation of weak learners. This approach utilizes discriminative characteristics by examining several parts of the input picture. Rather than doing a comprehensive exploration of the whole search space of potential visual characteristics, they advocate for the use of intelligent heuristics to expedite processing time and select pertinent aspects from the picture that enhance detection rates. The meta-heuristics include genetic algorithms, particle swarm optimization, random walk, and an innovative hybridization of these techniques. The findings achieved in the context of an intelligent transportation system demonstrate significant improvements in computing time, efficiency, and accuracy. Table 1 depicts the comparison of re- viewed literature as shown below.

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Table 1. Comparison of reviewed literature

Authors [Ref.]	Techniques	Outcome
(Liu et al., 2025)	KNN	The findings indicate that this technique exhibits superior recognition accuracy and generalization performance.
(Wang et al., 2025)	HHOSVM	The suggested model attains an accuracy rate beyond 98.10% with just five training samples per state, indicating a 27.48% enhancement compared to six current models.
(Lateef et al., 2024)	SA-BSO	The effectiveness of ontology matching with SA-BSO proves useful for sensor ontology alignment with general ontologies particularly in conference planning scenarios according to statistical data.
(Zhang et al., 2024)	Few-shot learning	Experimental findings indicate that our MetaDiff surpasses the leading gradient-based meta- learning approaches in few-shot learning challenges.
(Tianbo et al., 2023)	Flocking algorithm	The neighbor observation for group speculation is enhanced by using the adaptive gain control approach and a partial Kalman filter.
(Pazho et al., 2023)	Internet of Things (IoT)	Ancilia seeks to transform the surveillance domain by providing more efficient, intelligent, and equitable security solutions, fostering safer communities while preserving individuals' privacy rights.
(Wang et al., 2022)	Faster R-CNN	GNMOT along with ByteTrack represent the advanced multi-object tracking (MOT) models which serve to execute complete testing and validate performance across datasets and evaluative metrics.
(Alrowais et al., 2022)	KSA	Experimental findings demonstrate that MDTL-ICDDC presents better performance than Gabor and all other models including BoW-SRP, Bow-LBP, GLCM-SVM, GoogleNet, VGGNet.
(Usmani et al., 2021)	DL	Our methodology enables tracking stability and strengthens the tracking process robustness which reaches an accuracy of 97.09%.
(Alqaralleh et al., 2020)	RNN-T	The suggested RNN-T model is run by each sensor node, while the cluster heads implement the tracking algorithm to monitor the animals.
(Benabderrahmane et al., 2017)	Adaboost	The findings achieved in the context of an intelligent transportation system demonstrate significant improvements in computing time, efficiency, and accuracy.

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METHODOLOGY

This paper introduces a dual tracking solution through the combination of optical flow with swarm Intelligence and meta-learning. The tracker named KLT uses optical flow techniques to track the dominant points of target objects in frames starting from the first one until the final frame but the PSO (Particle Swarm Optimization) tracker that relies on swarm Intelligence simultaneously tracks the boundary information of target objects from frame 2 through the finish. The combination of tracking operations gives trackers superior resistance to the previously stated problems. We establish dominant points in the target object during frame one before tracking continues to the last frame. The polygon generates target object boundaries starting from frame 2 at runtime. Straight-line segments which connect the dominant points of the target object make polygonal approximations in every frame. Many randomly dispersed particles can be observed in frame-2 throughout the complete image search region. The swarm-based swarm distributes across all portions composing the dynamically formed polygon which defines the target object. The swarm formation pattern on each line segment develops through the minimum distance measurement of particles to their associated segment.

Data collection forms the initial phase of the process through the acquisition of diverse datasets which are relevant to the operation. The acquired data needs preprocessing through cleaning processes followed by normalization procedures to reduce inconsistencies. The extraction phase relies heavily on KLT at its current operation point. The dimensionality reduction approach KLT uses data variance as an efficient method to identify principal components within the data. It transforms the data into a lower-dimensional subspace while retaining the most significant features. This not only reduces the computational complexity but also improves the learning process by eliminating redundant or irrelevant features. As a result, the dataset becomes more manageable and informative for subsequent stages.

The reduced and optimized features are passed to swarm intelligence optimization, where PSO is employed. PSO, inspired by the social behaviors of birds or fish, is an evolutionary optimization technique. In this context, PSO optimizes feature weights, model hyperparameters, or even the KLT-based feature subset. Each particle (solution) in the swarm explores the search space, adjusting its position based on individual and collective best solutions, eventually converging to an optimal configuration. The combination of PSO yields a system which optimally adjusts both features and hyperparameter parameters to reach peak accuracy and operational effectiveness. The detection methods conduct qualitative data collection about user reactions and contextual aspects and project targets by employing surveys and interviews and observational analyses. All engineers, managers and tunnel builders form part of the participants group. The evaluation of each detection methodology requires assessments based on user experience together with assessments of practicality along with assessments of limitations along with evaluations of ambient conditions and project requirements.

The optimized feature set and hyperparameter values are then passed to the meta-learning phase, which focuses on learning to learn. Meta-learning acts as the intelligence layer that tailors the model-building process to the dataset's unique characteristics. It leverages prior knowledge or insights, such as selecting appropriate learning algorithms or architectures, to adapt the pipeline dynamically. Meta-learning algorithms can explore various model architectures and training configurations, guided by the results of KLT and PSO, to develop models that generalize well to unseen data. In the model creation phase, the machine learning model is constructed using the optimized features and hyperparameters. The iterative process of hyperparameter tuning further refines the model, ensuring it is configured for peak performance. This step benefits significantly from the integration of PSO, as it continues to guide the tuning process, identifying ideal values for learning rates, regularization terms, or other critical parameters.

A performing model moves to the evaluation phase forasive testing through validation methods coupled with accuracy-related metrics and F1-score or mean squared error. Among all models

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evaluated during the selection phase the most successful model receives final selection to correspond with the end of optimization and learning processes. In the deployment phase the chosen model gets integrated into a real-world application for generating practical predictions. This pipeline benefits from KLT, PSO, and meta-learning integration because the methodology acquires stronger capabilities to process high-dimensional data while optimizing learning settings and adapting response strategies for specific tasks. This combination of components leads to the production of highly performing reliable efficient models which suit various real-world applications.

A visual representation of image classification appears in Figure 2. The standard deep learning-based object detector development process requires a sequence of five steps which begin with image data acquisition followed by model type selection and preprocessing data and training the model and finally evaluating the model effectiveness. This research adopts a comparable development approach to which it adds evaluation and refinement steps. The core goal of this paper serves to develop an object detector system which enables benchmarking different inference techniques.

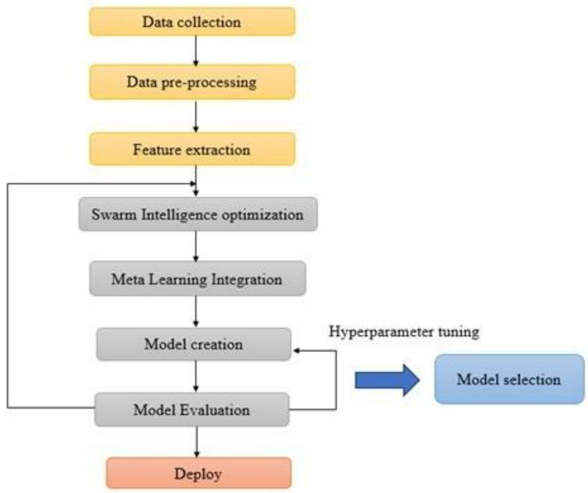

Figure 2. Flowchart of proposed framework

Data Processing

Data preparation is essential for data analytics. Outliers and noise may arise from inadequately controlled data collection. The analysis of such data will significantly compromise the pipeline's accuracy. Occlusions and overexposure must be taken into account in machine vision. A variety of data preparation techniques will be used to refine the dataset, ensuring the model con- serves computational resources by excluding unnecessary data. The dataset must be constructed in alignment with the stated models' framework requirements and input dimensions. The model requires that the pictures conform to its specified input size requirements. Consequently, the input parameters have been optimized for the model training input to enhance accuracy.

Kanade-Lucas-Tomasi (KLT)

The fundamental concept of KLT tracking may be elucidated by examining two photos inside an image sequence. Every basic KLT algorithm starts with finding corners or interest points satisfying the equation Shi and Tomasi (Misra & Ray, 2023).

$$\min(\lambda_1, \lambda_2) = \lambda \quad (1)$$

Where λ_1, λ_2 are two eigen values and λ is a predefined threshold.

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Assume the first picture is acquired at time t and the subsequent image at time t + τ. The incremental time τ is contingent upon the video camera's frame rate and should be minimized. A picture may be expressed as a function of the variables x and y. Let us denote a window in an image captured at time t+τ as I(x,y,t+τ). The fundamental premise of the KLT tracking method is;

$$I(x, y, t + \tau) = I(x - \Delta x, y - \Delta y, t)$$

(2)

The second time-domain signal results from point shifting throughout the whole first time-domain signal as per equation (2) $(\Delta x, \Delta y)$. This amount can be defined as the displacement $d = (\Delta x, \Delta y)$ and the main goal of tracking is to calculate d.

Algorithm

We summaries the KLT algorithm as follows –

Step 1: Find the dominant points which satisfy min (λ1, λ2)>λ.

Step 2: For each dominant point compute the displacement to the next frame using Lucas Kanade method.

Step 3: Record the displacement of each dominant point and update its status in terms of velocity and position provided its neighbor has better solution (see Section 3.3).

Step 4: Go to step 2 until all dominant points are exhausted.

Particle Swarm Optimization

PSO serves as an optimization method that launches its initial population by enabling "particles" known as biological creatures to search through different areas during their evolutionary process. The components that build PSO systems have built-in abilities to exchange information with their surrounding environment. All particles determine their position autonomously through past understanding that extends to also incorporate neighbor information. Optimal positioning by the particle led to mutual advantage between it and its neighboring particle. The PSO approach fulfills criteria for both regional and international search strategies. Through its operation the PSO algorithm seeks optimal parameters within current times. Particle swarm optimization algorithms have become popular recently because they offer high accuracy and fast convergence and easy implementation. PSO Algorithm performs its operations as shown in Figure 4.

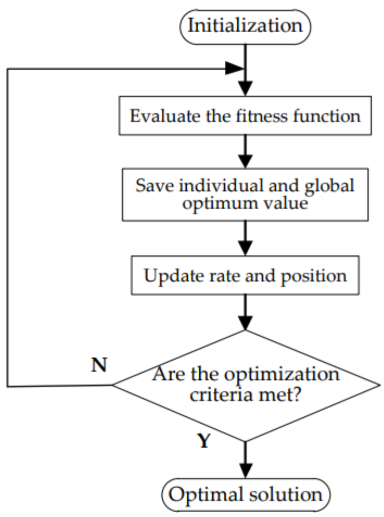

Figure 4. Schematic structure of the PSO algorithm

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PSO operates through two connected components which are Position and Velocity. A particle determines its position through its individual velocity process. Position of individual particle i in the search space during time interval t is represented by Xi(t). The position updation formula exists as follows:

$$Xi(t+1) = Xi(t) + Vi(t+1)$$

(3)

Where, Vi(t+1) is the velocity of particle I at time (t+1), which is computed based on this following formula:

$$Vi(t) = Vi(t-1) + C1.R1(P_{LB}(t) - Xi(t-1)_{-} + C2.R2(P_{GB}(t) - Xi(t-1))$$

(4)

The variables C1 and C2 designate the relative comparative effects on social and cognitive aspects. These learning rates receive the name of weights and typically maintain a fixed constant value for balanced weighting between components. The random values R1 and R2 result in robust learning rate components to achieve stronger performance. The position known as P_{LB} represents the historical best location ever found by the ith particle throughout its search. The P_{GB} variable represents the historically best position of the swarm and constitutes the particle with the closest solution.

The PSO-based tracker identifies the dynamically changing target object polygon through continuous KLT-based improvement of dominant object points tracking. The conceptual framework of swarm net compares directly to a neural network when employing swarm of swarms for object tracking. Neural networks contain fixed connections between neurons where each weight needs to be set after extensive data processing. Neural networks lead to exceptional learning accuracy but learn only specific tasks as their primary principle. DTAM's swarm net performs without needing synaptic plasticity but maintains vital cognitive functions such as crystallized intelligence and fluid intelligence.

Dual Tracking Algorithm with Meta Learning (DTAM)

DTAM serves as an advanced optimization method that boosts object tracking performance through simultaneous operation of two tracking mechanisms by using meta learning. This method consists of two tracking subsystems where the primary follows object positions using certain predictions and the secondary manages uncertain conditions that may occur. The backup system within the secondary tracker serves to reset primary tracking operations while assuring improved precision for demanding situations. DTAM tends to combine with machine learning models to achieve environment dynamism adaptation and precision enhancement. The system contains two parallel tracking layers which protect against data failure throughout the tracking sequence. Fig. 4 illustrates the representation of DTAM pseudocode in Figure 4 below.

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Algorithm 1 Dual Tracking Meta Learning (DTAM)

```
procedure DTAM (Video Sequence, with   Target Object)
Frames ← CALL Algorithm Frame   Extraction (Video Sequence, with   Target Object)
 ▸ Extract frames from input video.
breakpoint ← CALL Algorithm BrPt Calc (Frames) ▸ Calculate Breakpoints of target objects.
Dominant tcls ← CALL Algorithm Dominant Pt (brpt) ▸ Calculate dominant points from breakpoints.
nSwarm ← Number of swarms
ss ← Number of particles per swarm
for particles ← 1 to ss do
for pi ←1 to ss do
     Initialize particle pi velocity and position
     Initialize p Best and g Best
     Compute Procedure Fitness Compute PSO (pi)
  end for
end for
 ▸ Meta-Learning for Adaptive Hyperparameter Tuning:
α, ω ← Learn optimal learning rate and inertia weight using meta-learning
 ▸ Use historical data and environment feedback.
for particle in swarm do
 ▸ Dynamically adjust ω and α:
if Tracking error increases, then
 ▸ Increase ω to encourage exploration
else if Tracking error decreases, then
 ▸ Reduce ω to focus on exploitation
end if
 ▸ Fine tune p Best and g Best using learned parameters
end for
for frame ← 1 to Frames do
for dompt ← 1 to domptls do
old_dmpt ← domptcls (dompt)
dominant pts ← CALL Algorithm klt (dmpt)
if dominant pts (dmpt) - old_dmpt (dmpt) = 0 then
New Dompts ← Dominant Point Reinitialization (Accepted Particles, domptcls)
    end if
   end for
end for
for swarm ← 2 to nSwarm do
   for pi ← 1 to ss do
     Accepted Particles ← Fitness Compute PSO (pi)
     if pi NOT in Accepted Particles, then
     Update velocity of pi using Eq. (2)
     Update position of pi using Eq. (1)
    end if
  end for
end for
CALL Algorithm Bounding Box (Accepted Particles) ▸ Draw bounding box based on particles from
Accepted Particles vector.
end procedure
```

Figure 4. Proposed algorithm

The proposed algorithm describes object tracking methodology through a systematic sequence which integrates swarm intelligence and meta-learning techniques as illustrated in Figure 4. The algorithm starts by accepting an input video that contains the video feed for object tracking purposes. Through frame extraction the video splits into independent frames so each frame gets processed sequentially. Before tracking begins the pre-processing stage applies noise reduction together with normalization methods to improve the extracted frame quality. At this point the Kanade-Lucas-Tomasi (KLT) method executes feature extraction by tracking dominant feature points in each frame. The selected points play an essential role in tracking an object's movement and its relative position. The extracted features become input to the PSO-based swarm intelligence tracking method. This system applies Particle Swarm Optimization (PSO) tracking technology through which multiple particles optimize accuracy by continuously adjusting their positioning to monitor object boundaries

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in real time.

The system conducts meta-learning optimization following swarm intelligence object tracking to adjust to new settings and enhance tracking resilience towards lighting changes together with occlusion and motion variations. The system operates guidance optimization through learned knowledge to develop tracking parameters that boost model productivity during real-time operations. The object position refinement step brings together KLT feature extraction, PSO-based tracking data to achieve precise object positioning and drift correction.

The object tracking output reveals a precise position of the tracked object inside the video feed and appears as depicted in Figure 5. At the end state the tracking cycle reaches its conclusion point. A comprehensive tracking system emerges through the integration of KLT feature tracking with PSO swarm intelligence and meta-learning adaptive learning processes which results in resistance against complex dynamic conditions.

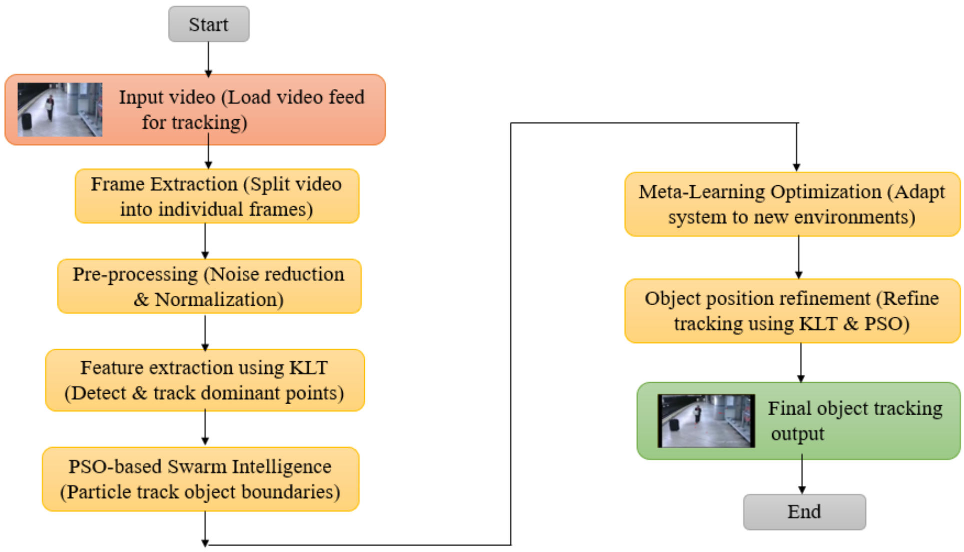

Figure 5. Proposed Flowchart

EXPERIMENT RESULTS

The experiments demonstrate the performance evaluation of this proposed method when compared to established state-of-the-art algorithms. The assessment of the proposed approach includes evaluation of accuracy and loss values from the training and validation phases to determine its effectiveness along with robustness. One video stream with a static background and high to moderate interest's motion selects from the experimental test data. Red dots within Figure 6 signify the dominant points chosen for object tracking that focuses on people along with luggage and structural components. The selection bases arise from three possible methods of edge detection alongside continuous movement parameters in the observed scene.

The dual tracking approach (KLT + PSO) illustrated in Figure 7 shows how a moving person gets tracked in static background scenarios through both Kanade-Lucas-Tomasi (KLT) feature tracking and Particle Swarm Optimization (PSO). Feature points labeled by the KLT algorithm appear as green dots because they use optical flow to track dominant positions automatically for reliable movement tracking. Meanwhile, the red dots indicate swarm particles generated by the PSO algorithm, which optimizes tracking by dynamically adjusting particle positions to refine the object's location.

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Figure 6. Our Proposed algorithm output

Figure 7. Dual approach (KLT+PSO) output

Table 2 presents a comparative analysis of the proposed algorithm against three existing methods—MDNet, CREST, and DTAM—based on training and validation results. The metrics used for evaluation include accuracy and loss for both the training and validation phases. The experimental results of MDNet demonstrate suboptimal performance through a training accuracy rate of 0.63 and loss value of 0.89 yet a validation accuracy rate of 0.62 with a loss of 0.86. CREST exhibits limited training (0.51) and validation (0.50) accuracy performance along with moderate loss values (0.73 and 0.68) reflecting its reduced capability levels. The performance of DTAM surpasses its counterparts by delivering 0.85 training accuracy along with 0.14 loss which corresponds to validation accuracy of 0.88 and validation loss of 0.11. The proposed method leads all current techniques by delivering maximum training and validation accuracy levels at 0.94 while maintaining very low loss values of 0.12 and 0.09 respectively. Among all considered algorithms the proposed method demonstrates the best performance combined with high robustness because it achieves lower loss and superior outcomes.

Dataset

Object Tracking Evaluation (2D bounding-boxes) Dataset: The object tracking benchmark consists of 21 training sequences and 29 test sequences. Despite the fact that we have labeled 8 different classes, only the classes 'Car' and 'Pedestrian' are evaluated in our benchmark, as only for those classes enough instances for a comprehensive evaluation have been labeled. The labeling process has been performed in two steps: First we hired a set of annotators, to label 3D bounding boxes as tracklets in point clouds (https://www.cvlibs.net/datasets/kitti/eval_tracking.php).

Long-Term Visual Object Tracking Benchmark datasets: We propose a new long video dataset (called Track Long and Prosper - TLP) and benchmark for visual object tracking. The dataset consists of 50 HD videos from real world scenarios, encompassing a duration of over 400 minutes (676K frames), making it more than 20 folds larger in average duration per sequence and more than 8 folds larger in terms of total covered duration, as compared to existing generic datasets for visual tracking (https://amoudgl.github.io/tlp/).

Human Tracking & Object Detection Dataset: The dataset comprises of annotated video frames from positioned in a public space camera. The tracking of each individual in the camera's view has been achieved using the rectangle tool in the Computer Vision Ansnotation Tool (CVAT) (https://www.kaggle.com/datasets/trainingdatapro/people-tracking/data).

Table 2. Comparison of Proposed algorithm with other existing methods

Algorithm	Training result		Validation result	
	Accuracy	Loss	Accuracy	Loss
MDNet (Nam & Han, 2016)	0.63	0.89	0.62	0.86
CREST (Song et al, 2017)	0.51	0.73	0.50	0.68
DTA (Misra & Ray, 2023)	0.85	0.14	0.88	0.11
Proposed method	0.94	0.12	0.94	0.9

The figure shows different models analyzed according to their training accuracy and loss measurements. The proposed approach delivers the highest training accuracy at 0.94 and proves to handle training loss at its lowest point according to Figure 8. The DTA model operates effectively because it delivers both high accuracy and minimal loss during training sessions. Analysis shows that the proposed method obtains better training accuracy and displays lower training loss than MDNet and CREST models which suggest inferior learning effectiveness compared to the proposed method. The proposed method proves its excellence through its high accuracy achievements and minimal training loss performance which demonstrates its superior learning efficiency over existing models.

Figure 8. Comparison graph of Training accuracy and Loss

Figure 9 depicts the validation accuracy and validation loss statistics which compare various models among each other. The proposed technique demonstrates both highest validation accuracy approaching 0.94 and lowest validation loss according to the figure presented. The DTA model demonstrates both high accuracies together with minimal loss in its performance. MDNet and CREST models demonstrate both poor validation accuracy and high loss which indicates weak generalization strength. The proposed method outperforms other methods regarding validation performance as it demonstrates superior accuracy retention alongside minimal loss to become the most effective method of validation.

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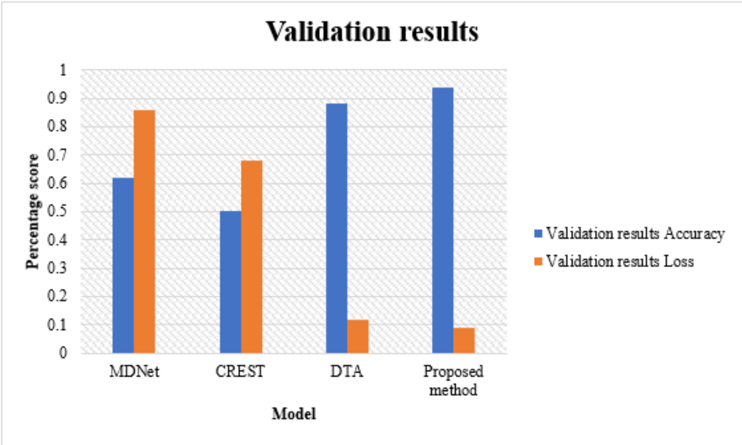

Figure 9. Comparison graph of Validation accuracy and loss

CONCLUSION AND FUTURE WORK

This research develops a dual-object tracking mechanism where KLT optical flow tracker works together with PSO tracker optimized by swarm intelligence yet strengthened through meta-learning strategies to deliver reliable tracking in complex scenarios. The proposed method overcomes important tracking problems linked with illumination changes and noise and sudden motion by combining the advantageous capabilities of KLT and PSO tracking methods. The KLT tracker enables the detection of key points on target objects across successive video frames at the same time the PSO tracker maintains boundary tracking capabilities to precisely locate objects regardless of environmental complexity. The implementation of meta- learning improves the model's learning procedure through task adaptation with small datasets so it can successfully handle different tracking problems. Experiments carried out on standard datasets revealed that the new tracking system surpassed existing algorithms in terms of performance which led to better precision rates and reduced system loss and better real-time adjustability. The results show the proposed dual-tracking system produces superior performance than conventional deep learning tracking approaches especially during unknown object appearance and environmental changes that require online adaptation without requiring thorough retraining.

The research demonstrates a cost-efficient and computationally effective solution for real-world object tracking through its integration between standard tracking methods and bio-inspired swarm intelligence models suitable for surveillance applications alongside autonomous navigation and human activity recognition systems. Future research directions may involve exploring hybrid deep learning architectures to further enhance the system’s performance, incorporating reinforcement learning for dynamic decision-making, and extending the framework to multi-object tracking scenarios with increased computational efficiency. The research findings deliver substantial contributions to computer vision through their introduction of a tracking framework which scales effectively with intelligent capabilities that track varied unpredictable environments accurately.

CONFLICT OF INTEREST

There was no conflict of interest declared by the authors.

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