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Ultra-Wideband Implementation of Object Detection Through Multi-UAV Navigation with Particle Swarm Optimization

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Abstract. Unmanned aerial vehicles (UAV) are widely used in literature for object detection utilizing convolutional neural networks (CNN). However, most UAVs make use of GNSS sensors for localization, which have low reception in indoor situations. Therefore, this study aimed to investigate the implementation of a multi-UAV object detection system and navigation with the aid of particle swarm optimization (PSO) in ultra-wideband (UWB) positioning systems for GNSS-denied environments, such as inside factories and warehouses. The performance of UWB systems was investigated to determine its viability in the PSO model. An object detection system based on the YOLOv5 network was trained with custom training images and subsequently evaluated with test images. The results of the object detection network were fed as inputs into PSO algorithms. Furthermore, different PSO algorithms were evaluated to determine the suitability for multi-UAV navigation and object detection. The results showed that UWB systems had sufficient accuracy for indoor localization, object detection, and navigation applications. YOLOv5 detection model detected objects with an F1 score of 0.93, given the optimal threshold of 0.8. Regarding the evaluation of PSO algorithms, the stochastic inertia weight variant of PSO algorithms (Sto-IW PSO) performed effectively across all metrics considered in the study compared to other algorithms that only performed effectively in one. Recommendations included the actual implementation of the system with multiple UAVs through field experiments and further refinements to PSO algorithms in order to match the kinematics and response time of the UAVs.

Keywords: Object detection; Particle swarm optimization; Unmanned aerial vehicle; Ultra-wideband

1. Introduction

Autonomous *Unmanned Aerial Vehicles* (UAVs) are gaining considerable study interest in recent years, as evidenced by various investigations on mapping applications (Li *et al.*, 2023; Yu *et al.*, 2022; Stachniss, 2009), search and rescue (Mishra *et al.*, 2021; Karaca *et al.*, 2018; Van-Tilburg, 2017), medical services (Nenni *et al.*, 2020), visual inspection (Nex *et al.*, 2022), and swarm applications (Preiss *et al.*, 2017). UAV systems have also significantly contributed to the growth of the *Internet of Things* (IoT) field by integrating numerous communication devices, sensors, cameras, and actuators (Motlagh, Taleb, and Arouk, 2016) to conduct various applications such as machine vision. Due to this, UAVs have played significant roles in the fourth industrial revolution in towards a sustainable future (Surjandari *et al.*, 2022) A key aspect that can be observed from the mentioned studies is

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the significance of Localization in facilitating the movement and data gathering of UAV systems.

Localization is the use of external sensors such as *Global Navigation Satellite Systems* (GNSS), vision, radio frequency, or RFID systems to identify the location of a tag in space and represent its coordinates. While GNSS sensors are effective in accurately locating UAVs within the search space, the performance drops in indoor applications due to the lack of line of sight to the satellites (Shule *et al.*, 2020). This limitation was also observed by Sandino *et al.* (2020), where the sensors failed to perform satisfactorily for indoor applications due to poor UAV localization. To address the limitation of GNSS localization for indoor applications, Badshah *et al.* (2019) investigated the use of cameras for Visual Localization. Although the system performed accurately, it required several cameras, as observed in the experimentation of Preiss *et al.* (2017), leading to a potentially costly implementation and complicated setup. In addition, the performance of visual systems is generally sensitive to lightning conditions of the environment. With the interest in local positioning systems for indoor UAV applications, there is a need for systems offering sufficient accuracy with a relatively simple setup. Among the types of technologies in local positioning systems, *ultra-wideband* (UWB) is preferred due to its high accuracy, wide range, low complexity, and low power consumption (Rajvanshi *et al.*, 2022; Hasan *et al.*, 2018). Tiemann, Schweikowski, and Wietfeld (2015) designed UWB-based indoor positioning systems with two-way-ranging and later utilized time difference of arrival in a subsequent study to reduce channel usage (Tiemann and Wietfeld, 2017).

In the context of UAV implementations, machine vision has been a significant study focus due to its contribution to industrial automation. The general process of object detection through machine vision mainly entails the extraction of features from an object, comparison with the image, and subsequent extraction of its position in the image, which can be translated to real-world location relative to the camera (Mansour, Dambul, and Choo, 2022; Jurado *et al.*, 2014). *Convolutional neural networks* (CNN) are often used to automate the extraction of these features and determine how the features can be used to classify or locate objects (Rawat and Wang, 2017). An effective CNN draws features from a large dataset and recent studies have combined them with other networks such as Long Short Term Memory for higher accuracy (Abdullah, Karim, and AlDahoul, 2023). Various research have shown success in the implementation of CNN to UAVs for image recognition with increased mobility (Zhu *et al.*, 2022; Zhong *et al.*, 2020; Nevavuori, Narra, and Lipping, 2019).

UAVs should be capable of quickly and reliably detecting objects in any environment in order to effectively implement object detection systems. These factors are evident in Sandino *et al.* (2020), which focused on search and rescue scenarios, demonstrating the need to minimize time when immediate assistance is required. The study also identified challenges related to operational time, often constrained by the limited battery supply of each UAV. Multiple UAVs can be utilized to address the time-sensitivity of missions, which can be supported with optimal path planning. Huang and Fei (2018) stated that *particle swarm optimization* (PSO) is relatively easier to understand and implement compared to other path planning algorithms. In PSO, each UAV is considered an individual particle in a search space where its movement depends on both personal experience and that of the swarm. Cho and Kim (2018) found that PSO outperformed genetic algorithms for single UAV and was comparable to non-hierarchical methods for multiple UAV applications. Multiple studies have reported success in the use of PSO for quadrotor path planning and navigation (Xu *et al.*, 2023; Shao *et al.*, 2020; Wang *et al.*, 2018). The flexibility of PSO algorithms was also demonstrated in other applications outside of robotics such as recognition of human activity (Zainudin, 2017). Mishra *et al.* (2021) saw success in combining PSO and CNN to achieve quick path planning and image recognition for time-sensitive search and rescue missions.

The current study aimed to address the aforementioned challenges by investigating the implementation of multi-UAV systems that utilized an optimized path determined by PSO and UWB positioning systems for localization in object detection tasks. The CNN object detector generated a confidence level indicating the probability of an object being within the bounding box on the captured frame, facilitating the localization of objects of interest. PSO was adopted to control the direction and velocity of UAVs for an efficient path to the object, with the cost function based on the results of designed object detection systems. Moreover, the study leveraged the benefits of radio localization through UWB localization systems.

2. Methods

2.1. Implementation and evaluation of UWB based positioning systems

Ultrawide-band positioning systems operate through radio localization, where multiple anchors placed around a controlled flight space communicate with tags placed on objects of interest, estimating the position of the tags through radio communication. The ability of UWB to communicate with multiple tags, estimate positions, and allow the relaying of positions to other tags is essential for multi-UAV applications such as object detection. In the current study, the performance of UWB positioning systems for multi-UAV was investigated by evaluating the accuracy of localizing UAVs. The effectiveness of UWB-based positioning systems could affect the performance of PSO in locating object-of-interest and in collision avoidance, which would be further discussed in the succeeding section. Crazyflie *Loco Positioning Systems* were the basis for this study as it utilized ultrawide-band technology. These systems adopted *Loco Positioning Nodes* as anchors and *Loco Positioning Decks* as tags placed on drones. The anchor nodes estimated distances using the Time Difference of Arrival of radio frequency waves, as shown in Equation 1.

$$d = c \times TDoA \tag{1}$$

where d is the distance from the beacon, c denotes the radio frequency, and $TDoA$ is the time difference of arrival (Mimoune, Ahriz, and Guillory, 2019). For this study, journal articles addressing the performance analysis of UWB systems using time difference of arrival were reviewed to determine the suitability as positioning systems for object detection adopting PSO.

2.2. Design and evaluation of a YOLOv5 convolutional neural network for object detection

YOLOv5 is a CNN-based object detector that relies on extracting image features to predict classification and regress bounding box. Among various detectors, YOLOv5 was selected due to its relatively fast test time while retaining a high mean average precision (mAP), crucial for real-time object detection on the image feed from drones (Nepal and Eslamiat, 2022). However, training the model requires fast-computing hardware and ample memory, which can be addressed by using a hosted notebook service providing access to sufficient computing resources. For the current study, the object to be detected is a white mug. A dataset comprising 200 images was collected at random locations, with half containing mug and the other half without mug. This verified whether the detector detected false positives in the testing stage. To detect the location of the mug, the image was manually annotated with a bounding box locating the object or a null when no objects were present. The dataset was divided into three sections, namely training, validation, and testing at 70:20:10 split. The training dataset was used for automated training of the

YOLOv5 detector with 270 layers. The number of anchor box sizes, attempting to enclose the object, was set to 6, and training was set to run for 150 epochs. Furthermore, validation dataset was used to provide an unbiased evaluation of the model while tuning its parameters. The test dataset was used to evaluate the final model after training. Once YOLOv5 object detection model for the white mug is complete, it would be used to determine and pinpoint the location of the object within a test area. Meanwhile, the confidence level would serve as a variable for UAV swarm path planning.

2.3. Design and evaluation of a particle swarm optimization algorithm for object detection

PSO served as the backbone to coordinate a swarm of UAVs to converge toward the object of interest. Each drone represented a PSO particle containing information on its position and velocity in x, y, and z coordinates. In each epoch, the drone, equipped with a hypothetical camera, attempted to utilize the object detection system to search for the object. The results of the object detection systems were used as the input for the cost function. Therefore, the local and global best solutions of the particles were used for updating position and velocity for the following epoch. The updated position was subsequently transmitted to the swarm, allowing individual drones to adjust position with the guidance of UWB positioning systems. This process iterated for multiple epochs until PSO algorithms converged to an optimal solution, where it detected the object of interest with a high confidence level. The cost function used in the study for PSO algorithms is shown in Equation 2.

$$cost = (1 - cl) + dis_{bbox} + ca \tag{2}$$

where cl is the confidence level of the detection, dis_{bbox} represents the normalized distance between the center of the bounding box from the center of the image, and ca is the collision avoidance factor. The cost function considered the results from the object detection system to guide the swarm toward the object of interest while preventing inter-UAV collisions. The cl indicated the certainty that object detection systems classified the object correctly. Subsequently, the resulting cl was subtracted from 1, where higher certainty corresponded to a lower cost. In cases where no bounding boxes were detected, the cost function should return 1 as the maximum cost. An appropriate confidence value would be determined through test runs with the object detection systems. The collision avoidance factor is set to 1 when UAV is within a minimum safe distance from another UAV, otherwise, the algorithm is set to 0. Also, ca can be neglected when there is enough height for each of the UAVs to set its own altitudes. PSO algorithms to be tested were derived from Kumar *et al.* (2013) and tabulated in Table 1, along with a brief description of the modifications from the standard PSO.

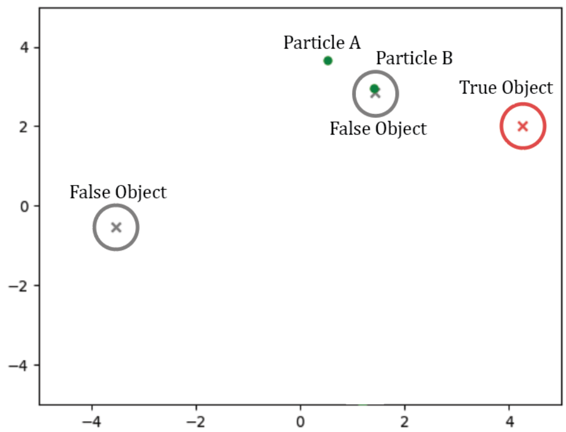


Figure 1 Simulation of PSO algorithms with two particles

Figure 1 presents a Python script that is initialized with three possible locations of the object of interest, where two are set as false objects with lower confidence levels. To introduce uncertainty regarding the location of the true object, the variable dis_{bbox} is considered in the cost function only when the particle is within 1 meter from the object, as shown by Particle B in Figure 1. Once the particle is within 1 meter from the object, the confidence level is added to the equation at a constant value. Each algorithm was evaluated based on the number of iterations until convergence, the average distance traveled by each particle, and the percentage of global optimum reached (Shankar, Kandath, and Senthilnath, 2021). Convergence is assumed when the best cost of all the particles is less than a tolerance value. Global optimum is assumed when the computed global best is within 1 meter of the true object at all dimensions. Each metric was based on the average of the results of 1000 runs, tested with three, four, and five particles. An overall score was computed to assess each algorithm performance in object detection. The conditions for a higher overall score are as follows: when the number of iterations and distance traveled are minimized, and the percentage of global optimum reached is maximized. Equation 3 evaluates the performance of each model.

$$\text{Score} = \frac{1}{3}\left(\frac{1000 - N}{1000}\right) + \frac{1}{3}(\%_{opt}) + \frac{1}{3}\left(\frac{D_{max} - D}{D}\right) \tag{3}$$

Where N is the number of iterations, $\%_{opt}$ is the percentage of global optimum, D is the average particle travel distance, and D_{max} is the highest obtained average distance from the eight algorithms. Equation 3 assumes that each metric is of equal importance.

Table 1 Algorithms considered for design of PSO

Algorithm	Brief Description
Standard PSO (S-PSO)	Standard PSO
Canonical PSO (C-PSO)	Updated velocity multiplied with constriction term
Hierarchical PSO (H-PSO)	Removal of inertial term. Reinitialize velocity when velocity becomes zero.
Time Varying Acceleration Coefficients PSO (TVAC-PSO)	c_1 and c_2 increases linearly every run
Hybrid HPSO and TVAC (HPSO-TVAC)	Combined H-PSO and TVAC-PSO
Stochastic Inertia Weight PSO (Sto-IW PSO)	Inertial weight randomized from an interval every run
Decreasing Time Varying Inertia Weight PSO (Dec-IW-PSO)	Inertial weight decreases linearly every run
Increasing Time Varying Inertia Weight PSO (Inc-IW-PSO)	Inertial weight increases linearly every run

3. Results and Discussion

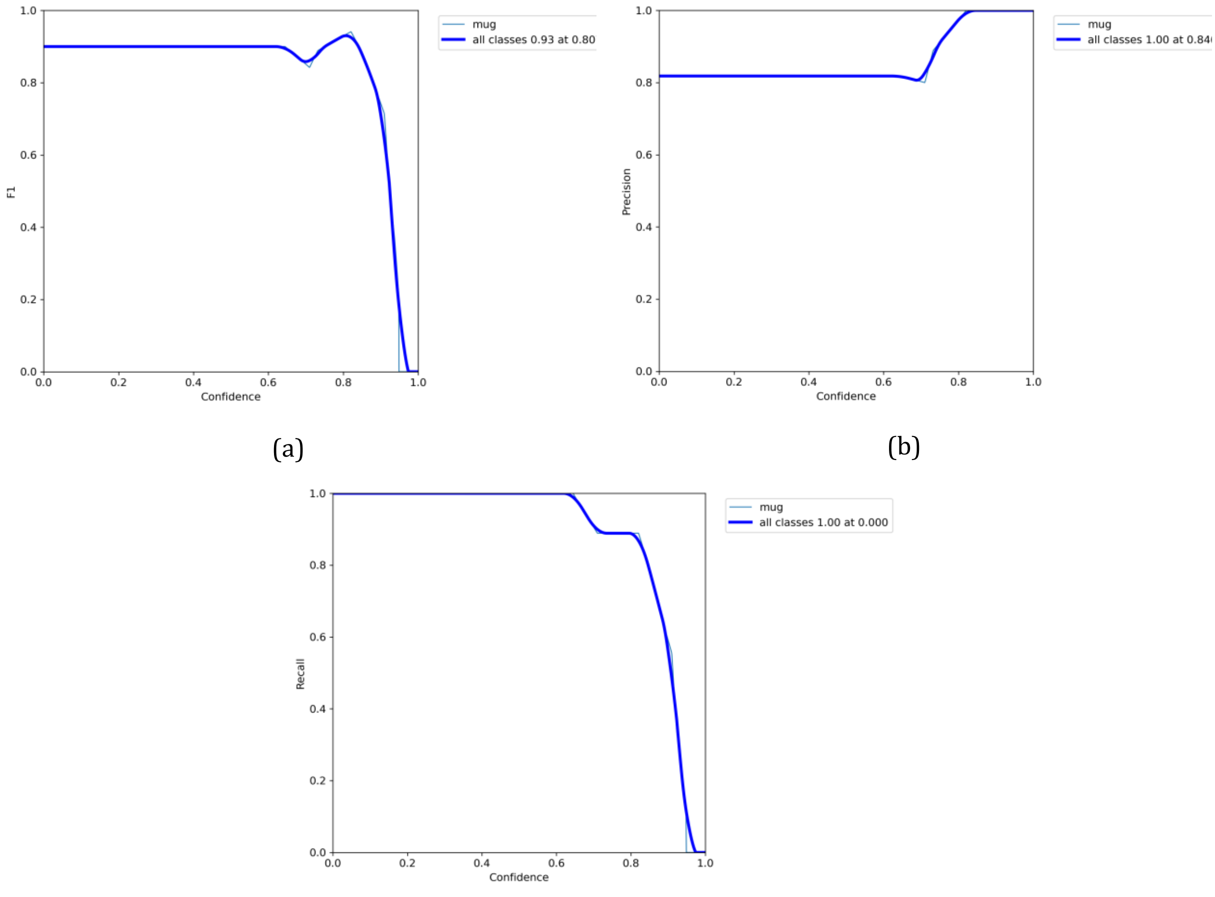
3.1. Studies on UWB performance on drone localization and control

Chu *et al.* (2019) showed that LPS only had an average relative error of 6.83% when 8 anchors were used. This error further decreased to 2.63% with a larger area. Similarly, Crețu-Sîrcu *et al.* (2022) successfully implemented UWB in a 14x40 m educational laboratory. For the purposes of PSO, UWB positioning systems were assumed to be implemented in a 10x10 meter space to control each drone accurately.

3.2. Evaluation of YOLOv5 object detection accuracy

The training of the model was completed in 0.082 hours using a Tesla T4 graphics card with 12 GB memory. After 150 epochs, the *mean average precision* (mAP) at 0.5 was 0.993, while the mAP in the range of 0.5 to 0.95 was 0.88. In the twenty test images, the model successfully detected 9 out of 9 images containing mug at a *cl* greater than 0.5, but 3 had a second bounding box of false positive. Out of the 11 images without mug, 8 were classified null, 2 as false positives less than 0.5 *cl*, and 1 as a false positive with *cl* greater than 0.5. Figure 2 shows the sample predictions from this test. The total processing speed of the model per image was approximately 5.4 ms. Based on the precision curve in Figure 3, maximum precision was achieved at 0.75 *cl*. However, the recall curve remained perfect until it dropped to 0.6 and subsequently decreased to 0 at 0.8. This indicated that exceeding a confidence level of 0.6 could result in some false negatives, while exceeding 0.8 would lead to an increase in false negatives. The F1 curve showed that the optimal *cl* was at 0.8, where the minimum false negatives and false positives were found.

Figure 2 Sample predictions of trained YOLOv5 model on test dataset.



(a) (b) (c)

Figure 3 Precision and Accuracy Curves on the Test Dataset: (a) F1 Curve, (b) P Curve, and (c) R Curve

3.3. Design and evaluation of object detection-based PSO algorithms

The algorithms were evaluated by simulating three objects at random points within a search space of 10 x 10 meters. The confidence values were set as 0.91, 0.69, and 0.42 based on Figure 2. The algorithms are terminated when the personal best cost for all particles is less than 0.1. The algorithms process the output from the object detection system, with the cost function considering the object with a higher confidence level when more than one possible object of interest is detected. In addition, the cost is normalized to [0,1], with 2 representing the maximum cost when no object is detected.

The performance of each algorithm is shown in Figure 4. Furthermore, Figure 4(a) shows that the number of iterations generally decreases as the number of particles increases. H-PSO had the least number of iterations at 391 for three particles, followed by Sto-IW PSO and S-PSO at 461 and 488 iterations, respectively. The performance of Inc-IW PSO improved with five particles, making it comparable with Sto-IW PSO and S-PSO. C-PSO was the longest to converge, requiring 615 iterations. However, increasing the number of particles significantly improved performance, surpassing Inc-IW PSO.

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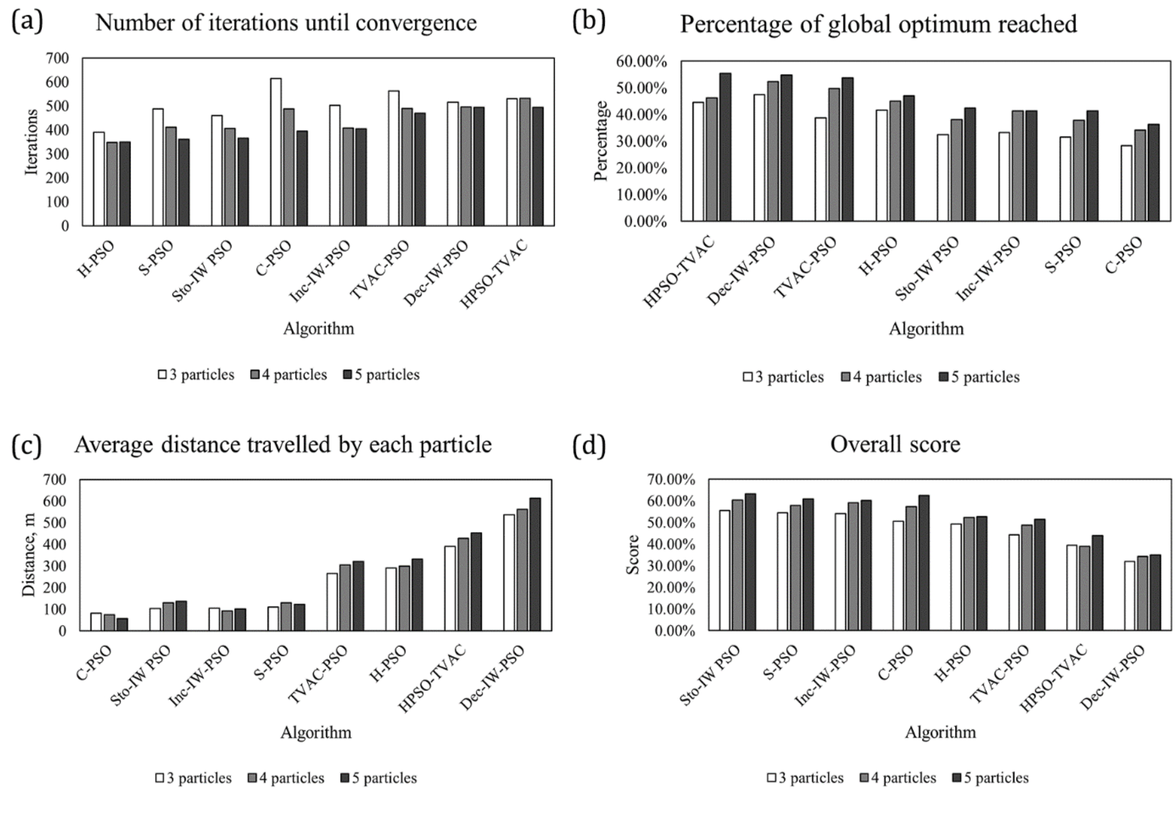

Figure 4 Performance of PSO algorithms in terms of (a) number of iterations, (b) percentage of global optimum reached, (c) average distance traveled by each particle, and (d) overall score

Figure 4(b) shows the results of detecting the true object from the three objects set. The increase in the number of particles improved the performance of each algorithm in detecting the true object. Models, such as Dec IW-PSO, HPSO-TVAC, and H-PSO exhibited percentages greater than 40%. Apart from H-PSO, the algorithms with fewer iterations showed less probability of reaching true detection. Dec IW-PSO and HPSO-TVAC both performed poorly in terms of convergence. H-PSO, on the other hand, showed an increase in performance to 47% when the number of particles was increased to five, surpassing HPSO-TVAC. In terms of the average distance traveled by each particle, as shown in Figure

4(c), C-PSO proved to be the most efficient, with an average distance of 83 meters for three particles, followed by S-PSO, Sto-IW PSO, and Inc-IW PSO, all traveling less than 200 meters. Increasing the number of particles led to an increase in the average distance traveled by each particle. Out of the top four performing algorithms, S-PSO had the most significant increase from 104 to 137 meters with five particles. Dec-IW PSO had the largest distance traveled, despite having the most global optimum reached.

The performance of the algorithms in the three metrics showed that focusing on a single metric compensated for other metrics. Figure 4(d) shows the computed overall score for each algorithm. Sto-IW PSO achieved the highest score for all number of particles considered, with 55.64% and 63.17% for three and four particles, respectively. Sto-IW PSO performed satisfactorily across all three metrics without significantly sacrificing accurate detections. Despite having high accuracy, Dec-IW PSO ranked the lowest due to its significantly higher particle travel distance compared to other algorithms. Adjustments could be made to the Sto-IW PSO algorithm to further improve accuracy.

4. Discussion

The performance of the different components in indoor multi-UAV object detection systems were presented in the earlier sections. For UWB-based localization, Chu *et al.* (2019) utilized Loco Positioning Systems from Bitcraze and recommended a minimum spacing of two meters spacing for the anchors to obtain accurate readings with an average relative error of 2.63%. Consequently, the simulated setup included anchors from Pozyx platform, used by Mimoune, Ahriz, and Guillory (2019), which were placed in four corners of the room 10 meters apart. This indicated that UWB localization systems could effectively supplement the performance of PSO by providing the model with relatively accurate pose data. To increase accuracy, UWB localization could be integrated into UAV control systems and fused with the onboard inertial navigation systems (Tiemann and Wietfield, 2017). Object detection systems can be implemented by mounting a camera on UAV, providing a bird-eye view of the search space. A pretrained YOLOv5 network can be used for common objects to reduce the time for the setup of the object detection system, as opposed to the one trained on custom data. The particles from PSO algorithm represent UAVs. Various PSO models were evaluated with the use case of the study, with Sto-IW PSO performing the best among the other models. However, adjustments may be necessary to better correspond with the kinematics and response time of UAVs. The computations for PSO algorithms can be carried out by the leader UAV. The cost function can be obtained from the output of the object detection system, comprising the confidence level of the detection and the distance of the object in the photo in pixels or meters when the camera parameters are known. Once the positions of the UAVs are computed, the leader UAV can transmit data to the follower UAVs to minimize computational load.

5. Conclusions

In conclusion, the performance of UWB-based localization, YOLOv5 detection network, and PSO was tested for viability in autonomous object detection through multi-UAV navigation. Studies on UWB systems demonstrated its suitability for indoor localization, particularly in areas not overly large with few obstructions. YOLOv5 was found to be effective in detecting specific indoor objects in various areas, with an optimal threshold of 0.8 enabling the swarm to locate the object with minimal false negatives and false positives. Most of the evaluated PSO algorithms could only perform satisfactorily on one metric. Minimizing the number of iterations would reduce the capability of the algorithms to reach the global optimum or decrease the distance traveled by each particle. Increasing the number of particles generally decreased the number of iterations and increased the probability of particles locating the actual object. However, this increased the average distance traveled by each particle. Sto-IW PSO performed satisfactorily across all metrics based on the overall score. By integrating these concepts, a system for multi-UAV object detection with UWB-based location could be devised. Future studies were recommended to focus on implementation through simulation or the use of actual robots. Furthermore, fine-tuning PSO for actual object detection could be carried out to improve accuracy and efficiency.

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