3D tracking of multiple drones based on Particle Swarm Optimization

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Abstract. This paper presents a method for the tracking of multiple drones in three-dimensional space based on data from a multi-camera system. It uses the Particle Swarm Optimization (PSO) algorithm and methods for background/foreground detection. In order to evaluate the developed tracking algorithm, the dataset consisting of three simulation sequences and two real ones was prepared. The sequences contain from one to ten drones moving with different flight patterns. The simulation sequences were created using the Unreal Engine and the AirSim plugin, whereas the real sequences were registered in the Human Motion Lab at the Polish-Japanese Academy of Information Technology. The lab is equipped with the Vicon motion capture system, which was used to acquire ground truth data. The conducted experiments show the high efficiency and accuracy of the proposed method. For the simulation data, tracking errors from 0.086m to 0.197m were obtained, while for real data, the error was 0.101-0.124m. The system was developed for augmented reality applications, especially games. The dataset is available at http://bytom.pja.edu.pl/drones/.

Keywords: unmanned aerial vehicle · drone · particle swarm optimization · multiple drones · multiple cameras · 3D tracking · 3D localization · motion capture · Vicon

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1 Introduction

Recently, the use of drones (also referred to as Unmanned Aerial Vehicles - UAVs) has significantly increased, both in civil and military applications. This is also the reason for the increased interest of researchers in various types of drone-related issues, including the problems of tracking these flying vehicles. The development of drone tracking methods is primarily driven by the need to develop effective systems for detecting, identifying, and disabling drones, which are currently extremely decent due to the increasing number of vehicles of this type [4]. These are primarily military and security applications. However, there are also other applications of drone tracking methods, e.g. augmented reality (AR) games [2].

There are many methodologies for detecting and tracking drones, but the most popular are: vision cameras, hyper-spectral images, radars, acoustic sensors, radio frequency techniques (RF), thermal techniques, and hybrid systems [4]. Among these approaches, optical methods stand out, which are considered the most convenient way to deal with this challenge due to their robustness, accuracy, range, and interpretability [17]. For example, Schilling et al. [10] proposed a vision-based detection and tracking algorithm that enables groups of drones to navigate without communication or visual markers. They equipped the drones with multiple cameras to provide omnidirectional visual inputs and utilized the convolutional neural network to detect and localize nearby agents. Another paper [17], presented an interesting concept of using two cameras (static wide-angle and low-angle mounted on a rotating turret) for autonomous drone detection and tracking. The single lightweight YOLO detector was used to detect drones. In [15], Srigrarom et al. described a multiple-camera real-time system for detecting, tracking, and localizing multiple moving drones simultaneously in a 3D space. They utilized a hybrid combination of the blob detection method and the YoloV3 Tiny model to detect drones on images and cross-correlated cameras to obtain global 3D positions of all the tracked drones. Another approach was presented by the authors of the study [8]. They introduce a real-time trinocular system to control rotary wing UAVs based on the 3D information extracted by cameras positioned on the ground. The drone detection and tracking are based on color landmarks and are achieved by using the CamShift algorithm. In [14], a hybrid detecting and tracking system that is made especially for small and fast-moving drones is proposed. In this method, a discrete-time Extended Kalman Filter (EKF) is used to track the positions and velocities of detected moving drones. The Kalman Filter is also used by Son et al. [13]. Sie et al. [12] presented the use of Correlation Filters and an Integrated Multiple Model (IMM) for filtering the position measurement of fast-moving drones. Another approach was proposed by Ganti and Kim [3]. They designed a low-cost system for detecting and tracking small drones. The system used low-cost commercial-off-the-shelf devices and open-source software. Moreover, it utilized image-processing algorithms to detect moving objects and the SURF method to distinguish drones from other objects.

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The review of the literature shows that there is a lack of published studies devoted to the problems of tracking multiple drones in three-dimensional space. In addition, no publications were found that measured the accuracy of 3D drone tracking. As far as we know, the Particle Swarm Optimization (PSO) algorithm has also not been used to track drones before. Hence, the development of a method for tracking multiple drones in 3D space and the proposal to use the PSO algorithm in it, are the main motivations for our work. We also prepared simulation sequences for testing the proposed drone tracking method.

2 A method for tracking multiple drones

The purpose of tracking is to obtain information about the position of the drone in the defined search space. If the drone is tracked in a two-dimensional image space, the complexity of the problem is relatively small and in this case, Kalman Filter [14,1] is often used. However, if the goal is to acquire a 3D position for many drones, the problem becomes much more complicated. For example, if four drones are to be tracked, the search space has 12 dimensions, while in the case of 10 drones, it already has 30 dimensions. In such cases, various optimization algorithms are used.

The proposed drone tracking method is based on the ordinary Particle Swarm Optimization algorithm [5], data from multiple cameras, and image processing methods used to extract the drone from the image. The PSO algorithm and its modifications have many applications, e.g. in signal and image processing, design and modeling, and robotics, as well as in problems related to motion tracking [7,6,9]. In the case of drone applications, flight controllers are the most common [16]. In order to estimate the exact position of drones in 3D space, the system requires at least three cameras, placed around the area in which the drones are moving.

2.1 Dataset

In order to evaluate the developed tracking algorithm, an appropriate dataset was collected. The dataset consists of three simulation sequences (S1, S2, and S3) and two real ones (S4 and S5), which differ in the number of drones and their pattern of moving on scene. The simulation sequences were created in an environment based on the Unreal Engine and the AirSim plugin [11], which is an open-source project created by Microsoft for high-fidelity simulation of autonomous vehicles. The scene for the simulation sequences was prepared using a model of the Human Motion Lab (HML) at the Polish-Japanese Academy of Information Technology in Bytom, in which real sequences were registered. The scene plan is presented in Fig. 1, except that the real lab contains only four cameras (cam_1, cam_2, cam_3, and cam_4) and the simulated lab contains all eight cameras. In addition, for the S3 sequence, the scene dimensions were doubled for the purpose of accommodating a higher amount of drones without an issue of potential collisions between each other. Statistics of sequences are

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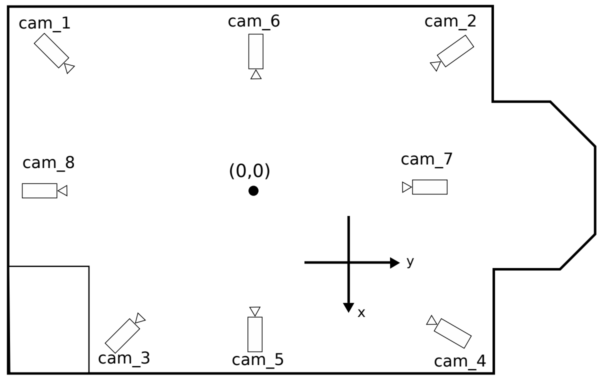

Fig. 1. Top view of the laboratory scene with the position of cameras

Table 1. Sequences metadata

seq. ID	#drones	#frames	length [s]	#cameras	resolution	FPS
S1	2	440	17.6	8	1920x1080	25
S2	4	215	8.6	8	1920x1080	25
S3	10	230	9.2	8	1920x1080	25
S4	1	1415	56.6	4	1924x1082	25
S5	1	2885	115.4	4	1924x1082	25

summarized in Table 1. Ground truth data for real sequences were acquired using a Vicon motion capture system. Calibration and synchronization of the motion capture system and video cameras were carried out using software and hardware provided by Vicon. The dataset can be downloaded from `http://bytom.pja.edu.pl/drones/`.

2.2 Particle Swarm Optimization

Particle Swarm Optimization is a metaheuristic method developed by Kennedy and Eberhart [5,6]. The concept of the method was taken from the social behavior of animals living in groups, such as shoals of fish, swarms of bees, or flocks of birds. In the PSO, the solution is found based on a set of particles, each representing a hypothetical solution to the problem. Each of the particles remembers the current position ($\mathbf{x}$), the velocity ($\mathbf{v}$), and the best position it has found so far ($\mathbf{pbest}$). In addition, the particles have access to the position of the best particle in the entire swarm ($\mathbf{gbest}$). The velocity $\mathbf{v}^k$ and $\mathbf{x}^k$ of the kth particle in the iteration t are updated using the following equation:

$$\mathbf{v}_{t+1}^k = \omega \mathbf{v}_t^k + c_1 \mathbf{r}_1 (\mathbf{pbest}_t^k - \mathbf{x}_t^k) + c_2 \mathbf{r}_2 (\mathbf{gbest}_t - \mathbf{x}_t^k), \tag{1}$$

$$\mathbf{x}_{t+1}^k = \mathbf{x}_t^k + \mathbf{v}_{t+1}^k, \tag{2}$$

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where $\omega = 0.75$ is the inertia weight, c_1, c_2 are the cognitive and social coefficients, respectively, equal to 2.05, and $\mathbf{r}_1$, $\mathbf{r}_2$ are vectors of random numbers in the range [0,1]. In subsequent iterations of the algorithm, the particles explore the search space and exchange information in order to find the optimal solution to the problem. The proposals are evaluated based on the fitness function (see 2.3). The initialization of particles in the first frame of the sequence is based on the known position of the drone. In subsequent frames, the position estimated in the previous frame is used to initialize the algorithm. The structure of the particle proposed for the purpose of tracking n drones is shown in Fig. 2.

2.3 Fitness function

The fitness function determines the degree of similarity of the solution proposed by the algorithm to the actual position of the tracked drones. For drone silhouette extraction the background/foreground detection algorithm proposed by Zivkovic and van der Heijden [18] and implemented in the OpenCV library was used. In addition, the images obtained in this way are subjected to morphological operations to remove noise and improve the extraction of the silhouettes of drones. In the next step, the hypothetical positions of drones, generated by the PSO algorithm, are projected into 2D image space, and then the rectangles (bounding boxes) approximating the size of the drones in the image from a given camera are determined. Having the bounding boxes representing the drones and the silhouettes of the real drones, their degree of overlap is calculated, and then the average overlap value for all drones in the image is established. Finally, the overlap value is averaged over all cameras. The process of calculating the fitness function for camera c can be described by the following equation:

$$f_c(\mathbf{x}) = \frac{1}{n} \sum_{d \in \mathbf{x}} g(\mathbf{I}_c(box_{c,d}))/size(box_{c,d}), \tag{3}$$

where $\mathbf{I}_c$ is the image with extracted drones for the camera c, n is the number of tracked drones, d is the drone in the particle $\mathbf{x}$ ($\mathbf{x}$ contains the positions of all drones), $box_{c,d}$ is a bounding box defining the drone d on the image of camera c, and $\mathbf{I}_c(box_{c,d})$ is part of the image representing the region of interest of $box_{c,d}$. The function $g(\mathbf{I})$ is defined as

$$g(\mathbf{I}) = \sum_{p} u(\mathbf{I}(p)), \quad u(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}, \tag{4}$$

where p is the pixel position in the image $\mathbf{I}$.

drone_1			drone_2				drone_i				drone_n		
x_1	y_1	z_1	x_2	y_2	z_2	$\cdots$	x_i	y_i	z_i	$\cdots$	x_n	y_n	z_n

Fig. 2. The structure of a particle

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3 Experiment results

The developed method for tracking multiple drones was tested on 5 video sequences with a different number of drones (see Sec. 2.1). The quality of tracking was assessed by analyzing both qualitative visual evaluations and using ground truth data. The experiments took into account different numbers of particles and iterations of the PSO algorithm. The estimation time of drone position for a single frame ranged from 0.02 to 1 second depending on algorithm configuration, number of drones, and number of cameras. The calculations were performed on a workstation equipped with Intel(R) Core(TM) i7-11800H and 64GB RAM.

3.1 Simulation dataset

The example tracking results for the simulation sequences are shown in Fig. 3, 4, and 5, while the obtained errors are presented in Table 2. The mean error value and the standard deviation calculated for individual sequences, averaged over

(a) S1_65 (b) S1_106

(c) S1_130 (d) S1_165

(e) S1_301 (f) S1_350

Fig. 3. Tracking results for selected frames of sequences S1, number of particles: 100, number of iterations: 70

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Table 2. Tracking errors for sequences S1, S2, and S3

		S1		S2		S3	
part.	iter.	mean [m]	std [m]	mean [m]	std [m]	mean [m]	std [m]
30	30	0.2525	0.3101	0.3567	0.5006	0.4676	0.3745
	50	0.1960	0.2177	0.2207	0.2586	0.3266	0.2463
	70	0.0857	0.0337	0.0965	0.1058	0.2670	0.2118
50	30	0.1419	0.1267	0.1972	0.2804	0.4823	0.3980
	50	0.1408	0.1261	0.1095	0.1293	0.2917	0.2212
	70	0.0859	0.0345	0.1065	0.1359	0.2267	0.1542
100	30	0.1413	0.1263	0.1804	0.2428	0.2970	0.2220
	50	0.1407	0.1261	0.0890	0.0925	0.2202	0.1686
	70	0.0859	0.0343	0.0784	0.0827	0.1972	0.1138

10 runs of the tracking algorithm are depicted. Depending on the configuration of the tracking algorithm and the sequence, the average tracking error obtained varies from 0.078 m to 0.482 m. As expected, the best results are obtained with the configuration with the highest number of particles (100) and iterations (70). For this configuration, the estimation time of the drones' positions for a single frame and sequence with 10 drones was approximately 1 second.

The smallest tracking error of 0.078 m was obtained for sequence S2, in which 4 drones were tracked. The algorithm in this configuration had 100 particles and 70 iterations. Analyzing the results obtained for the sequence with two drones (S1), it can be seen that for the configuration with fewer particles and iterations, worse results are observed than for the sequence with four drones (S2). This is due to the fact that in the S1 sequence, there is a situation in which the drones are very close to each other (Fig. 3(e)) and the algorithm has switched them in some runs. Increasing the number of iterations solved this problem. It is also worth noting that for the S2 sequence, the algorithm with the configuration of 50 particles and 70 iterations achieved an insignificantly worse tracking result than the configuration with fewer particles (30 particles and 70 iterations). This is due to the randomness of the algorithm. When analyzing the detailed tracking results of individual drones, it was observed that drone_1 has a larger tracking error for the configuration with more particles. This drone flies out of the field of view of some cameras, which causes tracking failure. For the configuration of 50 particles and 70 iterations, the problem occurred in four of 10 algorithm runs, while for the configuration of 30 particles and 70 iterations, it was only in three of 10 trials.

The worst results are obtained for the S3 sequence (0.197–0.482 m), which is primarily due to the large number of tracked drones, of which there are 10 in this case. Analyzing the detailed results for the configuration of 100 particles and 70 iterations (see Tables 3), it can be seen that for most drones the results are satisfactory (average error below 0.15 m), and the large error value is caused by difficulties in the tracking of drones number 1, 2, and 9. These are drones

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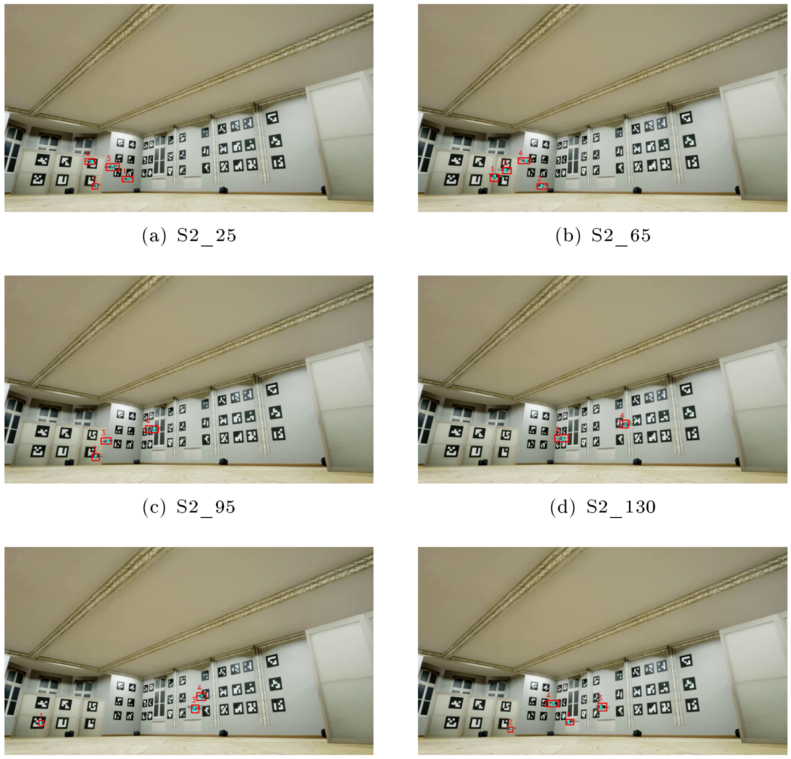

(a) S2_25 (b) S2_65

(c) S2_95 (d) S2_130

(e) S2_155 (f) S2_210

Fig. 4. Tracking results for selected frames of sequence S2, number of particles: 100, number of iterations: 70

that move on the edge of the scene, so they are not visible in some cameras, and at the same time they are far from the cameras on the opposite side of the scene, so they are smaller and contribute less to the value of the fitness function for a given camera (losing them has less impact on the value of the fitness function than in the case of a drone that is closer and therefore larger). In addition, drone_1 and drone_2 are flying close to each other (see Fig. 5), which resulted in substitutions, or the algorithm tracked one of the drones twice. Similar conclusions can be drawn by analyzing the graphs presented in Fig. 6, which shows the mean error value and standard deviation in subsequent frames of the sequence determined for 10 repetitions of the tracking algorithm. A large value of the standard deviation for some drones (drone_1, drone_2, and drone_9) indicates the occurrence of tracking errors in some of the algorithm runs. It can also be seen that for some runs the algorithm has temporary problems with tracking drone_5 around #40 and #110 frames and drone_10 near frame #200.

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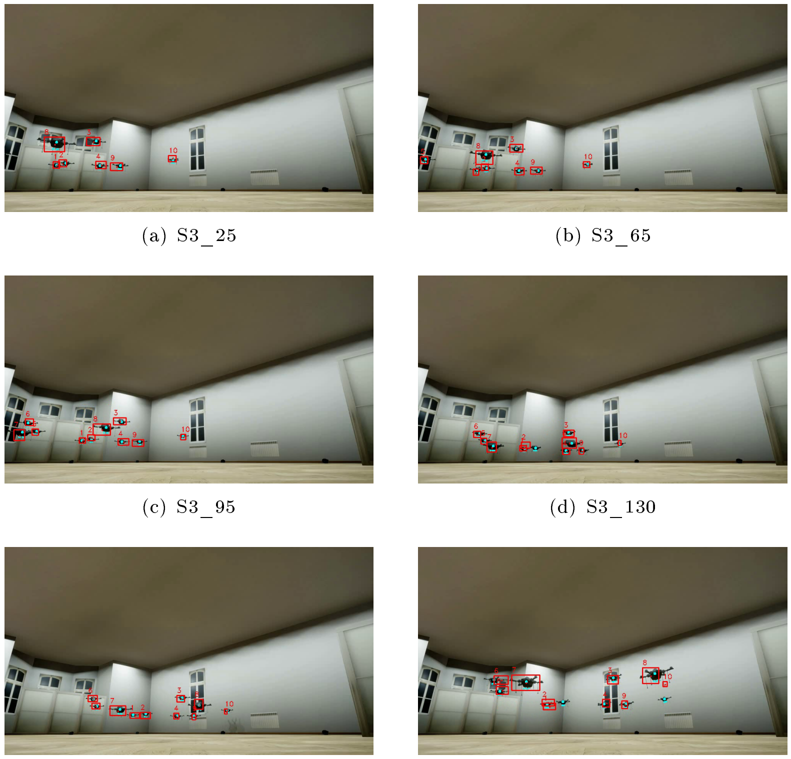

(a) S3_25 (b) S3_65

(c) S3_95 (d) S3_130

(e) S3_155 (f) S3_215

Fig. 5. Tracking results for selected frames of sequence S3, number of particles: 100, number of iterations: 70

Table 3. Detailed error statistics for sequence S3, number of particles: 100, number of iterations: 70

	mean [m]	std [m]	min [m]	25% [m]	50% [m]	75% [m]	max [m]
drone_1	0.3277	0.2116	0.0158	0.1157	0.3848	0.5039	3.7280
drone_2	0.5047	0.3560	0.0265	0.2216	0.4618	0.7104	4.3550
drone_3	0.1258	0.0516	0.0224	0.0904	0.1220	0.1544	0.3648
drone_4	0.1174	0.0507	0.0191	0.0830	0.1100	0.1470	0.3340
drone_5	0.1417	0.0891	0.0171	0.0873	0.1201	0.1680	0.9538
drone_6	0.1358	0.0647	0.0180	0.0896	0.1269	0.1722	0.5953
drone_7	0.1129	0.0471	0.0162	0.0803	0.1092	0.1402	0.4001
drone_8	0.1116	0.0528	0.0197	0.0766	0.1053	0.1353	0.6030
drone_9	0.2599	0.1276	0.0229	0.1776	0.2914	0.3400	1.2981
drone_10	0.1341	0.0866	0.0191	0.0813	0.1138	0.1566	1.2737
Mean	0.1972	0.1138	0.0197	0.1103	0.1945	0.2628	4.3550

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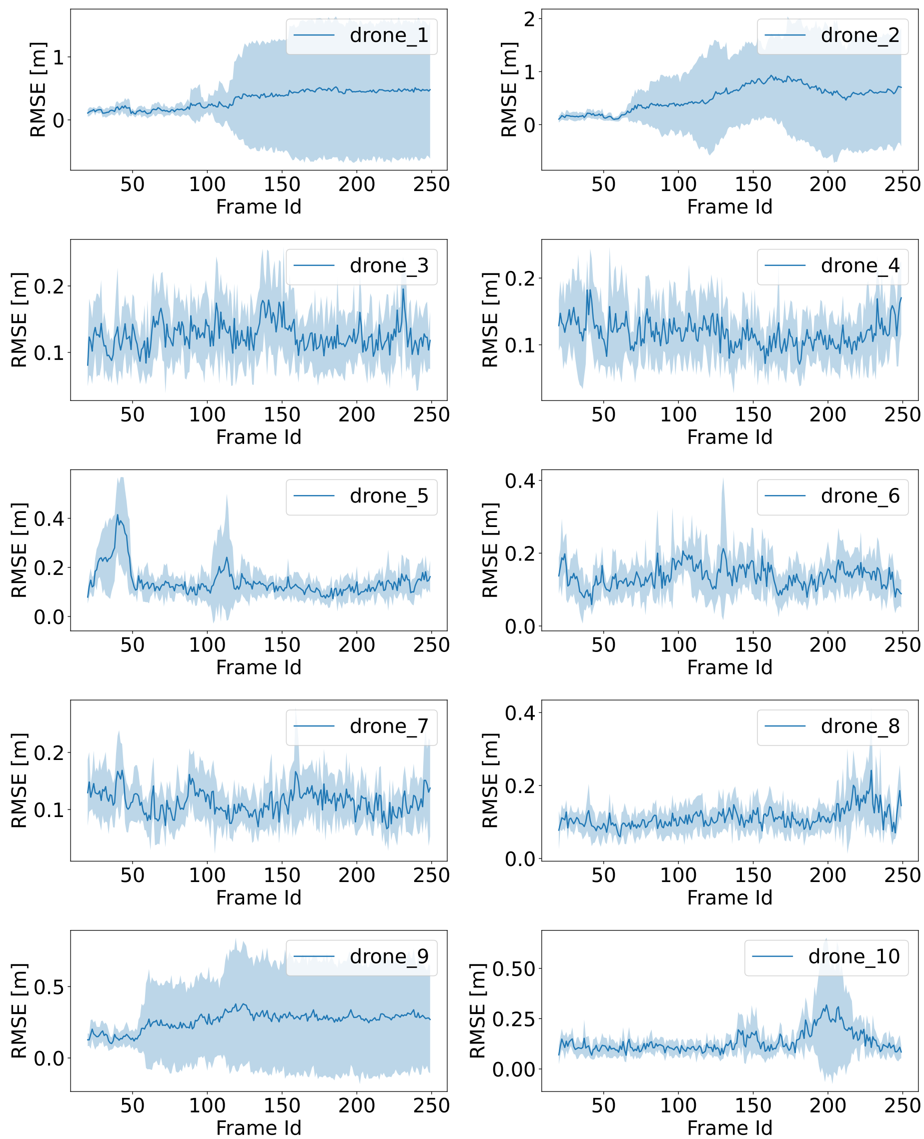

Fig. 6. Average tracking errors in consecutive frames for sequence S3, number of particles: 100, number of iterations: 70

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3.2 Real dataset

The example tracking results for the real sequences are shown in Fig. 7 and 8, while the obtained errors are presented in Table 4. In this case, we focused on the selected configuration of the algorithm (number of particles: 30, number of iterations: 20) and presented detailed results for it. For real sequences, a single drone was tracked, therefore the proposed configuration is sufficient. The number of drones has been limited to one due to space constraints in the laboratory, as well as the risk of collisions or damage to laboratory equipment in the case of a larger number of drones. These restrictions do not occur in simulation sequences. The errors obtained are similar to those obtained for the simulation sequences and range from 0.101 to 0.124m. It would seem that for a single drone, the errors should be smaller since for the simulation sequences with two and four drones errors of 0.08m were obtained. However, it should be noted, that in the case of real sequences, there are additional errors related to the inaccuracy of the motion capture system, synchronization errors, and calibration errors, which can be observed in Fig. 7(a), 7(d), 7(e),8(b), 8(c), and 8(e). In these cases, it may be noted that the position of the drone determined by the motion capture system (represented by the blue dot) does not coincide with the center of the drone. Another advantage related to the use of simulation sequences can be seen here.

4 Conclusions

In the paper, the method for 3D tracking of multiple drones was proposed. The presented approach uses Particle Swarm Optimization, image processing methods, and multi-camera data. In order to evaluate the developed algorithm, the dataset consisting of simulated and real sequences was prepared. The use of simulation sequences made it possible to evaluate the tracking method on sequences with a large number of drones (up to 10). The conducted experiments show the high efficiency and accuracy of the proposed method.

Despite obtaining satisfactory results, the method has some limitations. The main problem is tracking the drones at the edge of the scene where camera coverage is insufficient. This can lead to a decrease in accuracy or even loss of the drone. If the drones are close to each other, they can be switched. Another problem is related to the specificity of the background/foreground detection methods used in the objective function. If the drone stops moving, as a result

Table 4. Detailed error statistics for sequence S4 and S5, number of particles: 30, number of iterations: 20

seq.	mean [m]	std [m]	min [m]	25% [m]	50% [m]	75% [m]	max [m]
S4	0.1240	0.0490	0.0091	0.0915	0.1175	0.1488	0.5969
S5	0.1005	0.0362	0.0209	0.0747	0.0945	0.1205	0.4726

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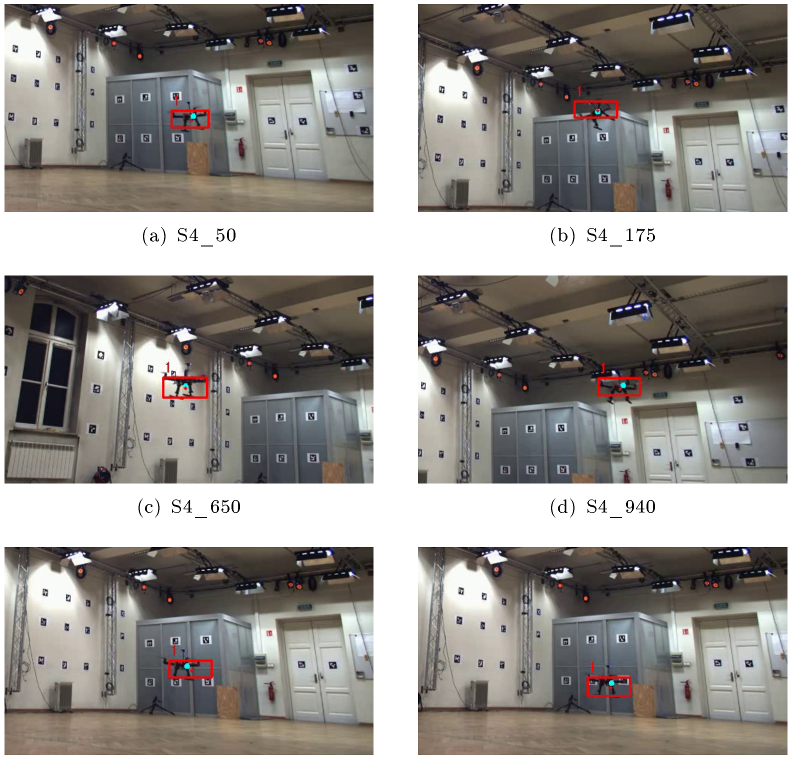

(a) S4_50 (b) S4_175

(c) S4_650 (d) S4_940

(e) S4_1265 (f) S4_1340

Fig. 7. Tracking results for selected frames of sequence S4, number of particles: 30, number of iterations: 20

of updating the background model, it will be treated as a background element over time and will disappear from the extracted images. Problems with drone extraction may also occur if it is similar in color to the background.

Future work will focus on improving the algorithm to remove or eliminate the described limitations by developing hybrid methods, that use other types of sensors than just video cameras.

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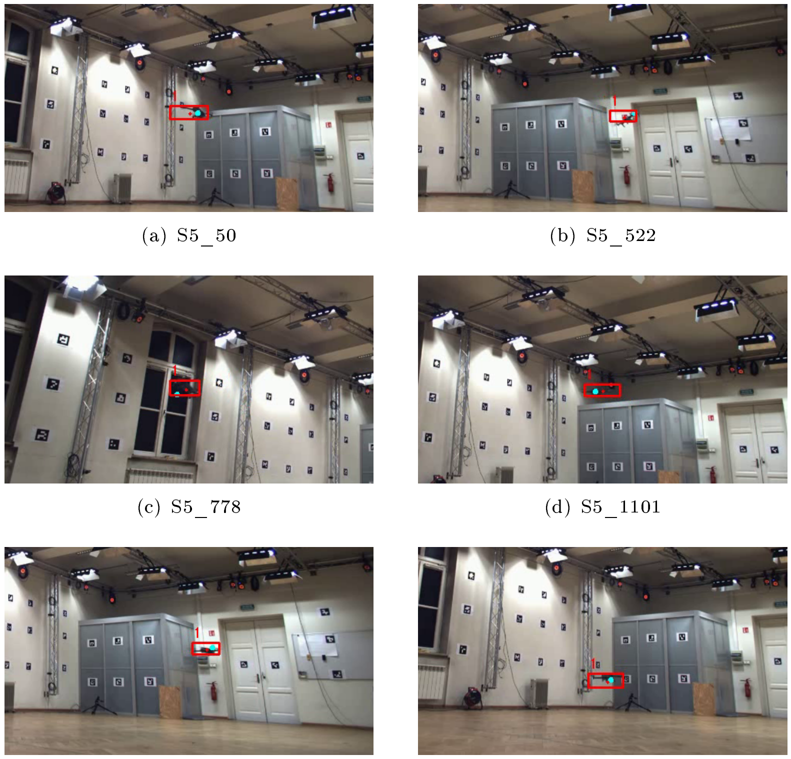

(a) S5_50 (b) S5_522

(c) S5_778 (d) S5_1101

(e) S5_2415 (f) S5_2830

Fig. 8. Tracking results for selected frames of sequence S5, number of particles: 30, number of iterations: 20

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