Multiple robots (robotic centers) and systems. Remote sensing and non-destructive testing

Роботизированные комплексы и системы. Технологии дистанционного зондирования и неразрушающего контроля

UDC 004.93'11
https://doi.org/10.32362/2500-316X-2022-10-5-38-48

RESEARCH ARTICLE

3D object tracker for sports events

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Abstract
Objectives. Sports events are currently among the most promising areas for the application of tracking systems. In most cases, such systems are designed to track moving objects in a two-dimensional plane, e.g., players on the field, as well as to identify them by various features. However, as new sports such as drone racing are developed, the problem of determining the position of an object in a three-dimensional coordinate system becomes relevant. The aim of the present work was to develop algorithms and software for a method to perform 3D tracking of moving objects, regardless of the data segmentation technique, and to test this method to estimate the tracking quality.
Methods. A method for matching information on the speed and position of objects was selected based on a review and analysis of contemporary tracking methods.
Results. The structure of a set of algorithms comprising software for a moving-object tracker for sports events is proposed. Experimental studies were performed on the publicly available *APIDIS* dataset, where a MOTA metric of 0.858 was obtained. The flight of an FPV quadcopter along a track was also tracked according to the proposed dataset; the 3D path of the drone flight was reconstructed using the tracker data.
Conclusions. The results of the experimental studies, which demonstrated the feasibility of using the proposed method to track a quadcopter flight trajectory in a three-dimensional world coordinate system, is also showed that the method is suitable for tracking objects at sports events.

Keywords: tracker, moving object tracking, FPV quadcopter, localization, tracking system

• **Submitted:** 02.06.2022 • **Revised:** 19.07.2022 • **Accepted:** 26.08.2022

For citation: Volkova M.A., Romanov M.P., Bychkov A.M. 3D object tracker for sports events. *Russ. Technol. J.* 2022;10(5):38–48. https://doi.org/10.32362/2500-316X-2022-10-5-38-48

Financial disclosure: The authors have no a financial or property interest in any material or method mentioned.

The authors declare no conflicts of interest.

НАУЧНАЯ СТАТЬЯ

Трекер объектов на спортивных мероприятиях

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Резюме
Цели. На сегодняшний день спорт является одной из наиболее перспективных областей для применения систем слежения за объектами. Большинство методов, на базе которых реализованы эти системы, ориентированы на отслеживание движущихся объектов в двумерной плоскости, например, для локализации игроков на поле, а также на их идентификацию по различным признакам. С развитием дрон-рейсинга актуальной стала задача определения положения в трехмерной системе координат. Целями работы являются разработка программно-алгоритмического обеспечения метода, позволяющего отслеживать траекторию движущихся объектов в трехмерном пространстве, абстрагированного от способа сегментации данных, и тестирование предложенного решения для оценки качества работы трекера.
Методы. На основе проведенного обзора и анализа современных методов отслеживания траекторий движения был выбран метод сопоставления информации о скорости и положении объектов.
Результаты. Предложена структура программно-алгоритмического обеспечения трекера движущихся объектов на спортивных мероприятиях и представлены результаты экспериментальных исследований на общедоступном датасете *APIDIS*, который включает в себя фрагменты видеозаписи баскетбольной игры, где по критерию качества отслеживания MOTA был получен показатель 0.858. Также были проведены эксперименты с использованием предложенного авторами датасета с пролетом FPV квадрокоптера по трассе. В результате по полученным с трекера данным была восстановлена траектория полета дрона в трехмерном пространстве.
Выводы. Результаты проведенных экспериментальных исследований показали, что предложенное решение позволяет отслеживать траекторию полета квадрокоптера в трехмерной (мировой) системе координат, а также подходит для слежения за объектами на спортивных мероприятиях.

Ключевые слова: трекер, слежение за движущимися объектами, FPV квадрокоптер, определение положения, система слежения

• **Поступила:** 02.06.2022 • **Доработана:** 19.07.2022 • **Принята к опубликованию:** 26.08.2022

Для цитирования: Волкова М.А., Романов М.П., Бычков А.М. Трекер объектов на спортивных мероприятиях. *Russ. Technol. J.* 2022;10(5):38–48. https://doi.org/10.32362/2500-316X-2022-10-5-38-48

Прозрачность финансовой деятельности: Авторы не имеют финансовой заинтересованности в представленных материалах или методах.

Авторы заявляют об отсутствии конфликта интересов.

INTRODUCTION

Contemporary tracking systems for moving objects are widely used in various social and industrial areas of human activity, e.g., the creation of autonomous vehicles [1], detection of motoring offences [2], provision of safety and security at mass gatherings [3], and personnel tracking [4]. One of the most promising areas of application of such systems is sports, especially team sports: football, basketball, etc. By tracking participants in sports events, it becomes possible to evaluate group tactical actions, predict the results of matches, etc. During the broadcast of football games, for example, movement monitoring is used to view personal replays or obtain extended player statistics [5].

To track the movements of athletes during the competition, it is necessary to solve two main tasks:
1) detection and identification of moving objects using sensors;
2) determination of the parameters (e.g., position and speed) of objects, according to which the path of the movement is reconstructed.

Player identification is complicated by the difficulty that athletes in team sports are often similar in appearance (e.g., due to wearing the same sports uniform). In addition, the movement paths of the players can change dramatically, resulting in occlusion and the need for re-identification. Thus, the main problem affecting the tracking accuracy indicators is the frequent switching of object identifiers [6].

Among the various methods and algorithms for tracking moving objects, multi-athlete tracking (MAT) technology can be distinguished. This video tracking system comprises several cameras acting as sensors to provide video data for subsequent processing. The literature covering MAT systems can be divided into two groups. Works in the first group [6, 7] are more focused on identifying characteristic features in order to solve the object identification problem, which often results in long delays in information output, while works of the second group [8, 9] are aimed at determining other parameters. However, the correct functioning of the MAT algorithms requires the determination of a spatial plane against which objects move, making it less appropriate for tracking objects in the air or moving across complex terrain.

A relatively young and actively developing sport is first-person view (FPV) quadcopter (drone) racing. This competitive sport is based on the speed and quality of passing a predetermined track with real-time video broadcast from the camera of the drone to the monitor, goggles, or pilot helmet of its operator. Due to the need to evaluate the flight trajectory for fair refereeing, tracking the movement path of objects in 3D space becomes an important consideration. For example, because of the high speeds involved, it is often impossible to visually determine which of the quadcopters passed the finish gate first. Most of the works on this subject are aimed at increasing the autonomy of quadcopters and developing algorithms for finding the optimal route, as well as testing them [10–12].

The purpose of the present work was to develop algorithms and software for a method for 3D tracking of moving objects that do not require identification at the detection stage and to test this method to provide an estimate of its tracking quality.

Our contribution is as follows:
- a moving-object tracker for sports events is proposed based on a described method for matching information on the speed and position of objects [13];
- experimental studies were carried out both on the publicly available *APIDIS* dataset, where a multiple object tracking accuracy (MOTA) metric of 0.858 was obtained, and on the presented dataset for quadcopter flight along a track;
- the 3D path of the drone flight was reconstructed.

1. REVIEW OF WORKS ON THE SUBJECT OF INVESTIGATION

Most of the works studying the problem of tracking moving objects are applicable to the development of athlete tracking systems. These mainly comprise methods that include a preliminary stage of detection, i.e., segmentation of data obtained from sensors in various ways. Since object identification is typically carried out at this stage, many studies are aimed at improving its accuracy by modernizing existing methods for searching for singular points and descriptors [14]. As well as describing the most frequently used descriptors and methods for detecting objects, Chigrinskii and Matveev [15] also studied approaches for improving certain aspects of the algorithms. Experimental results demonstrated higher tracking accuracy as compared with using basic methods. Approaching the problem of object localization using RGB color models, Lan et al. [16] significantly improved the performance of the system by training the descriptor at two levels: directly on the obtained image, as well as on its infrared representation. Such methods are not suitable for real-time implementation because of the need to train descriptors, which leads to a delay in the output of information.

Detection-based tracking methods can be divided into three groups according to the way they represent the shape of an object: points, geometric shapes, and contours (silhouettes). While the latter group of methods is more often used to track people (pedestrians, athletes, etc.) [17], the former, less resource-intensive, implementations are more suitable for other objects (cars, mobile robots, etc.). Volkova et al. [13] proposed a method for comparing information about the speed and position of objects, which allows them to be tracked in three-dimensional space. Identification is based on the obtained data on the speed and position of objects that can be represented as points, which is suitable for tracking small FPV quadcopters.

Wang et al. [18] proposed an online pedestrian tracking system. Segmented data are optimized by specifying the occlusion status. The position of the objects detected at the first stage is predicted using the Kalman filter, which, it should be noted, is often used in tracking algorithms. A comparison was made with the five most common trackers today (WVMF, SMOT-admm, SFCT, TLD, and DP + NMS). Experiments showed that the proposed system gives the best results. Linke et al. [19] compared two tracking systems in football: Gen4 and Gen5. The main difference between these systems is that Gen4 consists of two multi-camera systems, whereas Gen5 combines two stereo pairs on each side of the field and two monocular systems behind the goal areas. It was concluded that. the larger the number of cameras, the higher the accuracy of object tracking. On the basis of a comparative analysis of team sports tracking systems based on GPS data and multi-camera systems, Pons, et al. [20] concluded that higher tracking accuracy can be achieved with algorithms that use data from cameras.

Since many algorithms designed to solve the MAT problem require high-performance computers for their implementation, i.e., are costly [19], research is underway to create cheaper systems. Nishikawa et al. [21] proposed a tracking system based on the *k*-shortest path search algorithm. The results of the study proved the efficiency of the proposed solution when using relatively inexpensive cameras. Hui [22] investigated tracking the trajectory of sports objects using the mean shift algorithm. From the experimental results obtained, this approach demonstrated the possibility of reducing the required computing power.

Along with methods based on detection and identification, the MAT problem is often solved using algorithms based on the construction of occupancy maps. Taj and Cavallaro [23, 24] presented a tracking method based on a particle filter, where a priori information on the number of objects is not required. Liang et al. [25] and Yang et al. [26] used a hybrid method combining the construction of an occupancy map and the identification of the main features of the players. Although this approach provides a high MOTA, such methods are unsuitable for tracking quadcopters due to the need to implement a spatially deterministic plane.

Most studies of quadcopter flights along a track are aimed at increasing the autonomy of the flight to determine the optimal route [10–12], i.e., achieving superior technical vision and navigation. Moreover, there is an active development of datasets with complex trajectories containing a large number of sharp turns at high speeds [27], which significantly complicates tracking sports drones.

Thus, the results of the analysis performed suggest that to achieve the goal, the most appropriate approach for tracking the path of a sports object is based on comparing information about the speed and position of objects [13].

2. STRUCTURE OF ALGORITHMS AND SOFTWARE OF THE TRACKER

Figure 1 presents the structure of the algorithms and software of the tracker. In this work, it was decided to use only the main parameters, such as speed and spatial position (without using additional features) to reduce the delay in the output of information on objects.

A prerequisite for the tracker's operation is a preliminary calibration of all sensors, which determines the relative linear and angular displacements of the sensors' coordinate systems and chooses the origin of the world coordinate system. It is assumed that the position of the sensors relative to each other does not change throughout the tracker's work time.

The data obtained at the stage of object detection is fed to the tracker input. The result of the tracker is the state vector $\mathbf{x}_i$ of the object at time t. The vector consists of the basic geometric parameters (position L, speed V, and acceleration a; T is the transposition symbol) in the world (three-dimensional) coordinate system, as well as, if necessary, an identification number:

$$\mathbf{x}_i = (L, V, a)^{\mathrm{T}}.$$

Let us consider the blocks in the tracker structure. Table 1 compares the operations of the selected method and the blocks of algorithms and software.

The tracker algorithm consists of six blocks.

1. The input of the block "Creating a dataset on the position of objects" receives all segmented data on the position of objects O and O', comprising a set of projected vectors of coordinates of objects predicted using the Kalman filter in the coordinate system selected for localization. Thus, the output of the block is a set of vectors $O_t = \{O\ O'\}$.
2. The input of the block "Calculating the overall likelihood function" receives the data set O_t. Clustering in this case is performed by the mean shift method [24] and gives a set of clusters, the

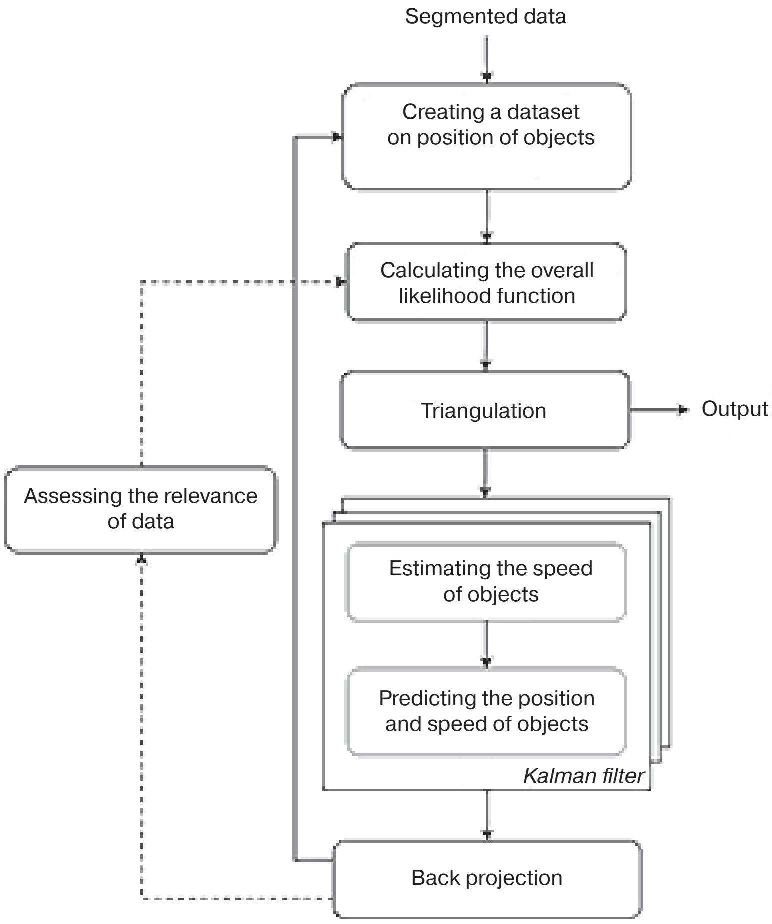

Fig. 1. Structure of algorithms and software of the tracker

Table 1. Comparison of the operations of the selected method and the blocks of algorithms and software of the tracker

Block	Operation
Creating a dataset on the position of objects	Creating a sample of observations O_t
Calculating the overall likelihood function	Calculating the overall likelihood function $p(O_t \| \mathbf{x}_i)$
Triangulation	Obtaining vectors $\mathbf{x}_i(L)$
Estimating the speed of objects	Obtaining vectors $\mathbf{x}_i(V)$
Predicting the position and speed of objects	Calculating vectors $\hat{\mathbf{x}}_i$
Back projection	Creating a sample of observations O'
Assessing the relevance of data	Calculating the parameter characterizing the reliability of obtained information A_{M}

number of which corresponds to the number of objects. The segmented data from the sensors are assigned identification numbers of objects that are in the same cluster.

3. In the "Triangulation" block, data with equal identification numbers from all the sensors are triangulated [28]. The output of the block gives the position of objects in the three-dimensional (world) coordinate system $\mathbf{x}_i(L)$.
4. The data obtained at the previous stage enter the third order Kalman filter block, which, in turn, consists of two blocks, the calculations for which are performed sequentially: "Estimating the speed of objects" and "Predicting the speed and position of objects" [29]. To estimate the parameters in a three-dimensional coordinate system, three Kalman filters are needed. When calculating the predicted parameters for the X coordinate, the following

expressions are used (for Y and Z, the expressions are similar):

$$\mathbf{A}=\begin{bmatrix}1 & T & 0\\ 0 & 1 & T\\ 0 & 0 & 1\end{bmatrix},$$

$$\mathbf{H}=[1\ 0\ 0],$$

$$\mathbf{x}_t=(L_X, V_X, a_X)^{\mathrm{T}},$$

$$\mathbf{Q}=\begin{bmatrix}\frac{T^4}{4\sigma^2} & \frac{T^3}{2\sigma^2} & 0\\ \frac{T^3}{2\sigma^2} & \frac{T^2}{\sigma^2} & T\sigma^2\\ 0 & T\sigma^2 & \sigma^2\end{bmatrix},$$

$$\hat{\mathbf{x}}=\mathbf{A}\mathbf{x}_t,$$

$$\hat{\mathbf{P}}_{t+1}=\mathbf{APA}^{\mathrm{T}}+\mathbf{Q},$$

$$K_{t+1}=\hat{\mathbf{P}}_{t+1|1...3,1}(\hat{\mathbf{P}}_{t+1|1,1}+\mathbf{R})^{-1},$$

$$\mathbf{x}_{t+1}=\hat{\mathbf{x}}+K_{n+1}(\mathbf{x}-\hat{\mathbf{x}}_{1,1}),$$

where $\mathbf{Q}$ is the process noise covariance matrix; $\mathbf{R}$ is the sensor noise matrix; $\mathbf{P}$ is the noise covariance matrix; K is the matrix correction factor; $\mathbf{H}$ is a matrix that defines the output data; $\mathbf{A}$ is the state matrix; T is the measurement period, σ is a filter parameter, which depends on the dynamic characteristics of the observed object.

At the output of the block, data are generated on the predicted position and speed of objects in the three-dimensional coordinate system.

5. The block "Back projection" reprojects the data obtained in step 4 from the world coordinate system into the coordinate system of each sensor O'.
6. The block "Assessing the relevance of data" calculates the parameter A_{M} characterizing the reliability of the received information. It is calculated as follows:

$$A_{\mathrm{M}}=\exp\left(-\frac{t_{\mathrm{m}}}{d\Delta Ts}\right),$$

where t_{m} is the time elapsed since the last determination of feature, ΔTs is the sensor measurement period, and d is the coefficient of decrease in the relevance of data.

If, at the moment of time t, the data of none of the measurements of the object or the data of only one measurement has been received (the latter is unacceptable for triangulation), then the predicted reprojected position and speed are indicated as the data received from the sensors in the block "Creating a dataset on the position of objects." The A_{M} parameter in this case is necessary to correct the tracking duration according to the predicted data, i.e., to timely stop tracking the object.

3. EXPERIMENTAL INVESTIGATIONS

In the first experiment, the *APIDIS*[1] dataset was used to verify the proposed algorithms and software. This comprised seven video segments of a basketball game, which were taken from different cameras located around the court. Two cameras (first and seventh) were chosen, having different focal lengths but both aimed at the same corner of the court. Segmented data on objects were obtained by a previously proposed method [30]. During the experiment, for one minute (a sequence of 1500 frames), the parameters of the position and speed were estimated for four preselected objects, which most often intersected with each other and with other objects.

In Fig. 2, the black lines represent the reference trajectories for all objects in space on the XY plane (in this experiment, the displacement along the Z axis is 0), while the colored lines represent the selected targets. The reference trajectories were obtained by interpolating the coordinates of the objects presented on the dataset website at an interval of 1 s.

Figure 3 presents the reference trajectories of the selected targets and the trajectories reconstructed on the basis of the segmented data received from the cameras. Table 2 presents the results of calculating the MOTA tracking accuracy index in comparison with other modern methods.

Table 2. MOTA indicators of various trackers

Tracker	MOTA
[6]	0.752
[31]	0.796
[32]	0.811
Tracker proposed in this work	0.858

Based on the analysis of Table 2, it can be concluded that the proposed algorithms and software of the tracker provide a high tracking accuracy and is superior to known analogues.

For the second experiment, a stand was constructed in our laboratory (Fig. 4).

[1] https://sites.uclouvain.be/ispgroup/index.php/Softwares/APIDIS. Accessed January 1, 2022.

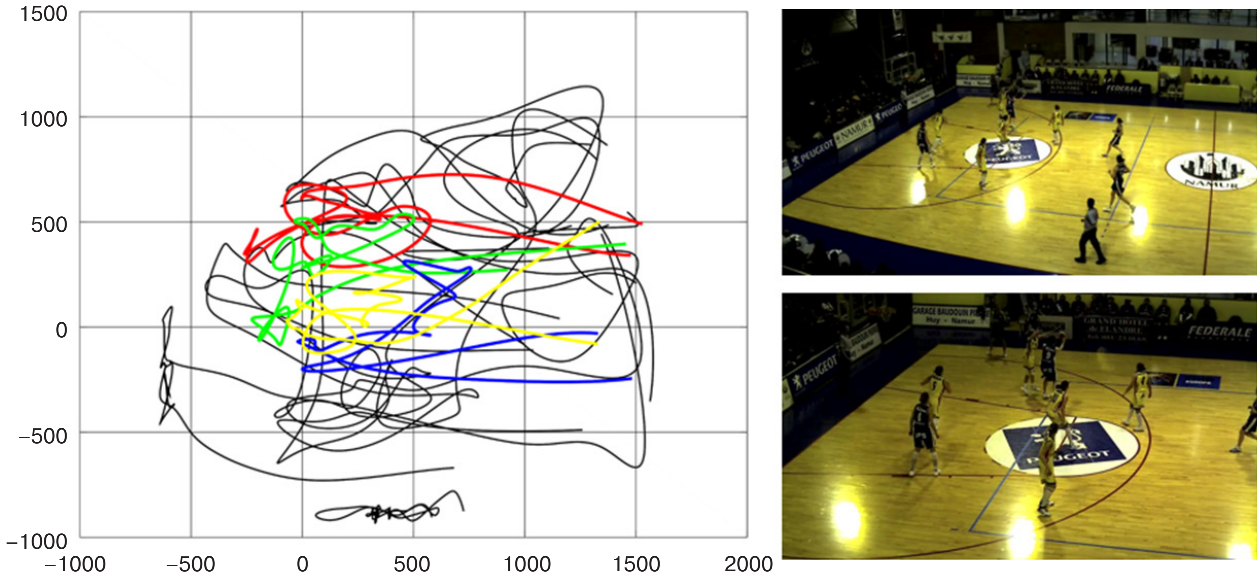

Fig. 2. Reference trajectories of players (left) and frames from the first and seventh cameras (right)

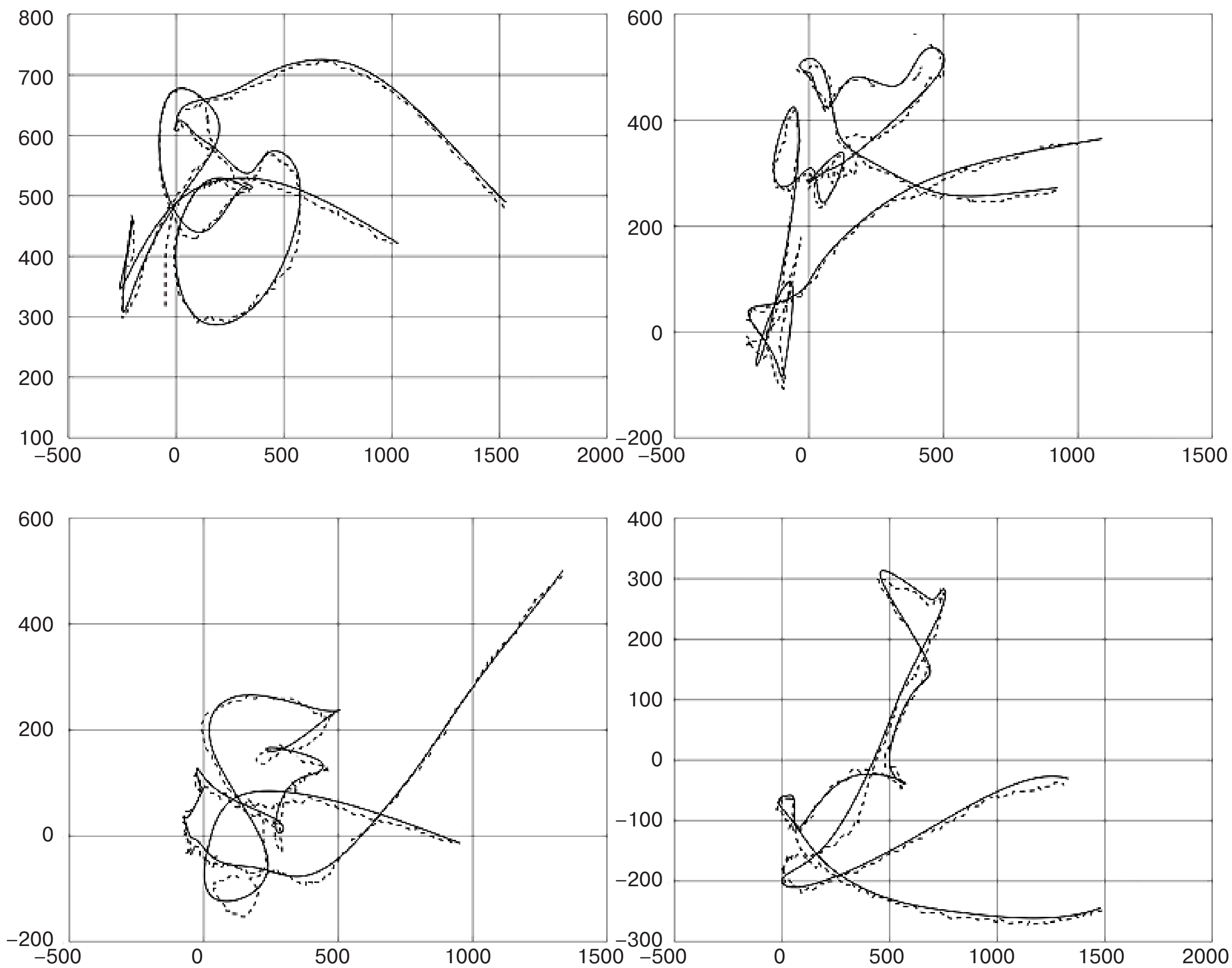

Fig. 3. Reference trajectories of objects (solid lines) and the trajectories reconstructed from segmented data (dashed lines)

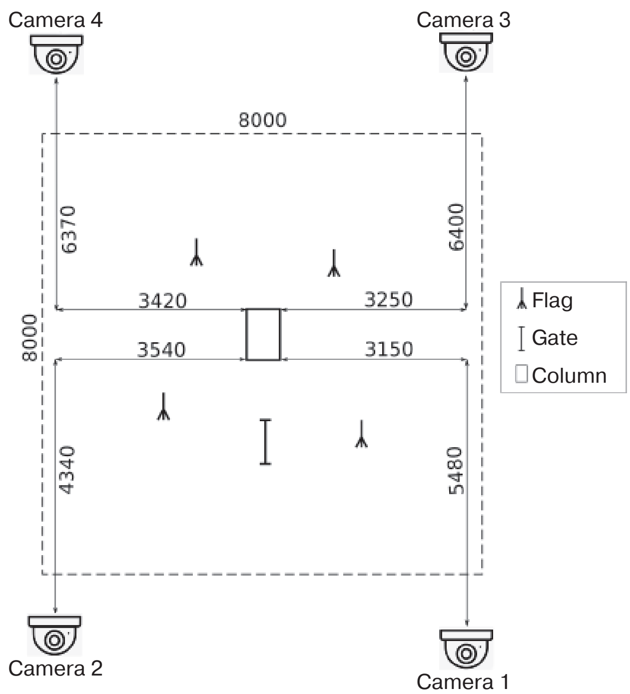

Fig. 4. Schematic of a test stand

The stand consisted of a video tracking system with four BD133 dome cameras (manufactured by Beward, Russia) and a quadcopter track. The track comprised five elements: four flags (range poles) and a gate. The dimensions of the working area were 8 × 8 × 3 m. Calibration of the cameras determined that the frame rate for the first camera should be 13 fps (frames per second), while for the other cameras, it should be 25 fps. During the experiment, a dataset was taken simultaneously from four cameras of the quadcopter Photon (manufactured by MIREA – Russian Technological University, Russia) flying along the track for 30 s. Segmentation of a moving object (quadcopter) was performed by the frame binarization method with a predetermined threshold. The quadcopter flight trajectory was reconstructed in the world coordinate system (Fig. 5). Then, for verification, this trajectory was projected back onto the images received from the cameras. The result is shown in Fig. 6.

The quadcopter flight trajectory was successfully restored. During the course of the experiment, it was also determined that the delay (latency) in the output of information for one object after the segmented data was sent to the tracker is 32 ms.

CONCLUSIONS

In this work, contemporary methods for tracking moving objects were reviewed and analyzed with special attention paid to MAT methods. The structure of a set of algorithms comprising software for the tracking of moving objects is proposed based on the

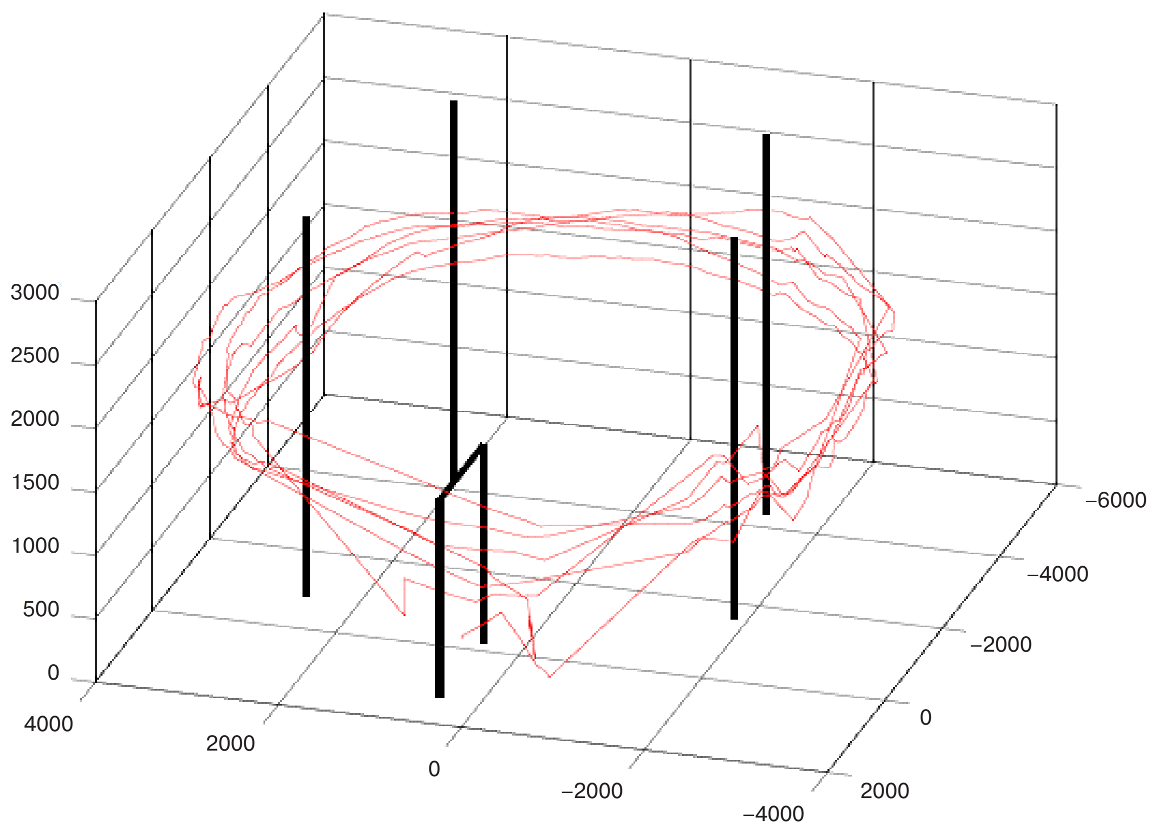

Fig. 5. 3D reconstructed quadcopter flight trajectory

Fig. 6. Frames received from cameras and the tracked quadcopter (marked with a red marker)

method of comparing information on the position and speed of objects. The experimental studies demonstrated the possibility of using the proposed solution to track a quadcopter flight trajectory in a three-dimensional (world) coordinate system, as well as being suitable for tracking objects at sports events.

ACKNOWLEDGMENTS

This research is supported by the RTU MIREA grant “Innovations in the implementation of priority areas for the science and technology development,” project No. 28/24.

Authors’ contributions

M.A. Volkova has proposed the solution for implementing the object tracker for sports events, presented the results of experimental studies on the APIDIS dataset and a test stand, conducted an experiment with a quadcopter flying along the track, and written the text of the article.

M.P. Romanov has proposed the solution for implementing the object tracker for sports events.

A.M. Bychkov has presented a test stand and conducted an experiment with a quadcopter flying along the track.

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Translated from Russian into English by Vladislav V. Glyanchenko
Edited for English language and spelling by Thomas A. Beavitt