

Retraction

Retracted: Soccer Player Video Target Tracking Based on Deep Learning

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] B. Zheng, "Soccer Player Video Target Tracking Based on Deep Learning," *Mobile Information Systems*, vol. 2022, Article ID 8090871, 6 pages, 2022.

Research Article

Soccer Player Video Target Tracking Based on Deep Learning

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Soccer player video target tracking is a very challenging task, which has good practical and commercial value. Traditional soccer game target tracking relies on athletes to carry a recording chip to achieve target tracking, but the cost is very high. With the rapid development of photography technology and deep learning technology, athletes' target tracking is realized through soccer game video. Deep learning technology is applied to computer vision detection and tracking. How to realize soccer players' video target tracking under deep learning is a challenging lesson. To solve this problem, this paper takes the video target tracking of football players as the research object, collects the game images of the stadium through multiple cameras, realizes the long-term accurate tracking of multiple players, and establishes a multicamera multitarget tracking system. The KCF algorithm and the improved KCF algorithm formed by replacing the hog feature of the KCF algorithm with the depth convolution neural network are used to compare and analyze the impact of different target tracking ranges and target numbers on the target tracking accuracy of the system, so as to accurately obtain the motion trajectory of football players. The results show that the image data of football matches are collected independently by multiple cameras, and the data of multiple cameras are collected to generate each target motion datum. The KCF algorithm of multicamera multitarget tracking has good robustness and real-time for long-term accurate tracking of football players; the KCF algorithm and the improved KCF algorithm have high accuracy in target tracking. With the increase of tracking frame range, the accuracy of target tracking of the two algorithms is improved. At the same time, multitarget tracking helps to improve the antiocclusion ability of the system. The research results have important practical significance and good application prospects for the analysis technology of video content of football matches.

1. Introduction

With the development of the Olympic Games and the world cup, especially in the form of computer technology, the number of video clicks and the world cup are gradually improved. As the most ornamental sport, football is loved all over the world. The analysis of football game video mainly includes player tracking, player activity map, and referee video map [1]. The target detection and tracking of video is the key technology to realize these. Football videos often add various special effects to attract attention. Coaches and analysts analyze some motion data through videos. Players also want to watch their own game performance, and these behaviors need to rely on target motion trajectory extraction technology [2, 3]. For major football matches, these needs must be met one by one. Only by increasing the cost and increasing the investment of human and material resources

can they be realized. However, for some amateur football matches, low-cost target tracking schemes have more practical value and practical significance [4].

In the aspect of target tracking of football players, scholars at home and abroad have carried out rich research, from single target tracking, multitarget tracking, and multicamera multitarget tracking. Multicamera multitarget tracking has the advantages of obtaining large image acquisition area, solving occlusion, illumination change, and so on, but there are difficulties in multicamera data fusion and target matching [5, 6]. Some researchers have proposed a regional target matching method, which uses target features to match multiple cameras. Some researchers realize target matching based on color features and establish a Gaussian color model to match the target through the color histogram as the matching feature [7, 8]. However, when the target color is similar, the matching is easy to produce errors. At the same

time, when the light changes, the color will change and there may be great differences in the color of the same target, which greatly affect the target matching [9]. Some researchers propose to match based on the feature points of the target [10]. By taking the centroid of the target as the feature point and establishing a three-dimensional coordinate system, the position of the target is determined. Some scholars have proposed using SIFT features for target matching, which can effectively solve the impact of changes such as illumination, rotation, and reflection [11–13]. However, the feature extraction time is long and the algorithm requirements are very high. At the same time, the more the number of targets, the greater the calculation pressure.

With the development of computer vision technology, video target tracking has become a hot research field, but there are few mature algorithms [14]. This is because target tracking is greatly affected by the external environment, such as motion state, occlusion, and light, so it is very difficult to achieve fast processing speed and accuracy. With the maturity of deep learning technology, the target tracking algorithm based on deep learning is developing rapidly, and the accuracy is guaranteed [15]. Deep learning is a branch of machine learning, in which “depth” refers to the number of network layers in the neural network model. Some researchers use the method of deep learning to improve the accuracy of crack target recognition, which is 10% higher than the traditional method. Therefore, the model of deep convolution neural network gradually replaces the traditional image classification algorithm [16]. Some researchers have proposed the RCNN deep neural network model, which extracts the target area through selective search, uses the RCNN network model to extract the target features, obtains the detection frame through the trained SVM classifier classification and non-maximum suppression algorithm, and achieves good target detection results. However, when multiple targets need to be detected at the same time, the RCN runs slowly, which affects the detection effect; by improving the RCNN algorithm, some scholars have proposed a new network structure spp net, which greatly improves the running speed by transforming images of different sizes into feature vectors of fixed dimensions and only needs one RCNN target feature extraction [17]; on the basis of RCNN and spp net, some researchers proposed fast RCNN, which realized end-to-end training by adding softmax layer instead of SVM classifier. Some researchers have proposed the full winder RPN network, which can input the whole image and output the rectangular box containing the target [18]. At the same time, it can cover the whole image by using a variety of different sliding windows, and each sliding window can get the results of the probability and position regression of the target. In this paper, a set of multicamera multitarget tracking system is designed, which can accurately track multiple athletes for a long time by collecting the athletes’ stadium competition images. A multicamera multitarget tracking system is established. The KCF algorithm and the KCF improved algorithm are used to analyze the impact of different target tracking ranges and target numbers on the target tracking accuracy of the system, so as to achieve the soccer players’ video target tracking under the deep learning.

2. Research Method

2.1. Multicamera Multitarget Tracking Method. By tracking the players in the football video with a single camera, the area covering the football field is incomplete and the players will sometimes disappear and sometimes appear in the camera, which is prone to number matching errors. This paper adopts multicamera and multitarget tracking, collects the whole stadium through multiple cameras, processes the collected image data, and uses multiple cameras to obtain target information to ensure that the players are in the field of vision. The targets between multiple cameras can be corrected each other, when the number matching error of a player in one camera can be corrected by other cameras and finally the correct player can be matched back.

In football video, player tracking needs to obtain the trajectory of all players. Firstly, the coordinate system of each camera and the court and the mapping relationship between them should be established. At the same time, the camera position is fixed and the mapping relationship can be realized through camera calibration. The process of camera calibration (Figure 1) is as follows:

- (1) Install 12 cameras on the football field. The installation position is shown in Figure 2. Set the height and focal length to ensure that they can cover the whole football field.
- (2) Use the calibration plate to rotate the camera in different directions to ensure that the calibration plate can appear in all positions of the camera. At the same time, select 20 clear images and use Zhang’s calibration method to calibrate the internal parameters of the camera.
- (3) Simulate the movement of football, place the football with different colors from the football field, take one of the four corners of the football field as the origin of the coordinate system, and record the coordinates of the projection of the football center under the field coordinate system.
- (4) According to the image with football taken by the camera, the color is used to distinguish the football and the field and the coordinates of the football in the image are calculated.
- (5) The corresponding relationship between the pitch coordinates of football and the pixel coordinates in the image is obtained by calculating the internal parameter matrix and external parameter matrix.
- (6) Through the internal and external parameters of the camera, the pixel coordinates of the football are converted into coordinates. According to the error between the converted coordinates and the real recorded coordinates, the image is divided into regions to compensate the pixel coordinates.

2.2. Multicamera Fusion Algorithm. Through the multicamera fusion algorithm, the individual target tracking results of multiple cameras in a complete video sequence are

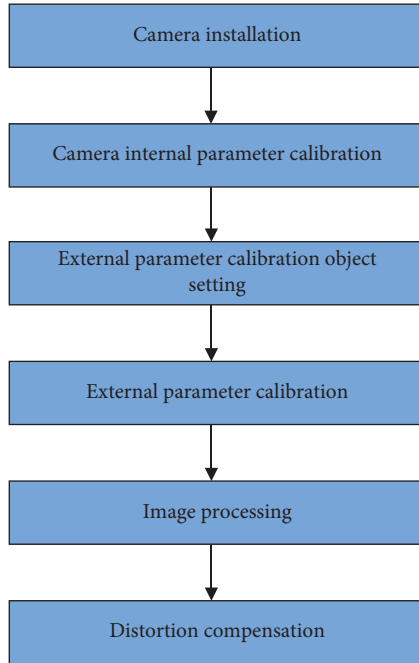


FIGURE 1: Camera calibration process.

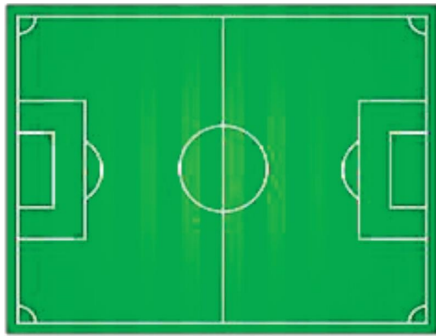


FIGURE 2: Camera installation location.

converted to each corresponding athlete through coordinate transformation. In order to improve the accuracy of fusion, a triple matching method is adopted, which uses historical information correspondence, nearest neighbor algorithm matching, and template matching.

Historical information matching is a mapping relationship, that is, the mapping between the target number under each camera and the real athlete number. The nearest neighbor algorithm line matching is measured by the target distance between the end position and the start position of the adjacent cycle to achieve the nearest neighbor algorithm matching. Template matching is to match objects by calculating the similarity between two images. After triple matching, the normalized correlation matching method is selected to realize multicamera fusion.

2.3. Multicamera Multitarget Tracking Algorithm Based on Deep Learning. In order to collect the images of the players in the stadium in real-time and output the motion

trajectories of the players in the stadium, the tracking of the players in the game is decomposed into multiple continuous tracking cycles. Each tracking cycle inputs a video clip (including continuous images of N frames, n is a constant), so as to save the motion trajectories of all players in this video clip and collect all tracking cycles to obtain the motion trajectories of all players in the whole game.

The multicamera multitarget tracking process is as follows:

- (1) For each tracking cycle, the N frames of images collected by a camera are input into the single-camera multitarget tracking module to obtain the initial position of each athlete. The movement track of athletes is fused with the movement track photographed under the camera of the previous cycle to obtain the movement track of each athlete and the target is numbered and saved. Repeat this operation for each camera to obtain the image motion track and its number of all athletes in the current cycle.
- (2) The player's image coordinate trajectory is mapped to the court coordinate trajectory, and the court coordinate trajectory of each player in this tracking cycle is obtained by the multicamera fusion algorithm. The data collected by multiple cameras can be synchronized with the data collected by multiple cameras in the next cycle. In the calculation process, the football is a fixed target. If the field coordinates of the football calculated by multiple cameras differ greatly, the single camera module has a target tracking error and the track can be deleted. At the same time, the volume of the football is small, the tracking is difficult, and it may be blocked frequently. There is no connection between the detected football trajectory. The missing ball trajectory between the two cycles is supplemented by linear interpolation. When the interval between the two weeks is large, the motion trajectory of the ball is kept missing.

The operation flow of the multicamera multitarget tracking method (Figure 3) is as follows: when the algorithm starts to run, 13 threads are run for parallel processing, the first six and the last six threads are used for image acquisition and singlecamera multitarget tracking, and the seventh thread runs the multicamera data fusion algorithm and integrates the data of the previous tracking cycle. Through cyclic processing, it will be completed automatically or manually.

3. Results and Analysis

3.1. Design of Multicamera Multitarget Tracking System. Through the deep learning algorithm, the multicamera multitarget tracking system can process the athlete's trajectory images collected by multiple cameras, extract the trajectory of each athlete and football, and store it in the database in the form of points. At the same time, the system also needs to have the function as shown in Table 1.

The system design is mainly divided into input layer, single-camera multitarget tracking module, multicamera

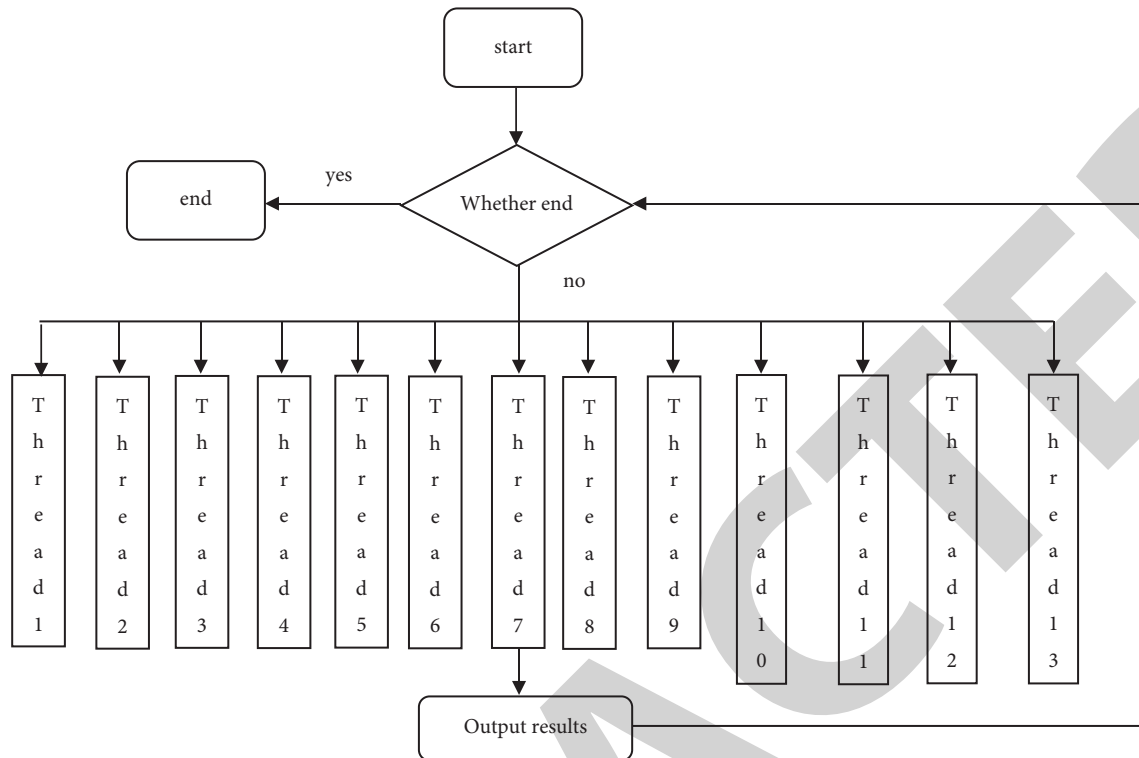


FIGURE 3: Operation flowchart of the multicamera multitarget tracking method.

TABLE 1: System function description.

System name	Function description
Multicamera multitarget tracking system	Real-time: the running speed of the program should exceed the image acquisition speed to avoid memory explosion.
	Robustness: the program should have high robustness, be able to deal with some interference, and ensure accurate tracking.
	Accuracy: the target position determined by the program is not far from that visible to the naked eye.
	Modularization: each module of the program is independent, which is convenient for later optimization and upgrading.

data fusion layer, and output layer. The input layer mainly inputs the image collected by the camera into the system. The single-camera multitarget tracking module realizes multitarget tracking for each camera to collect images. The multicamera data fusion layer corresponds to the fusion of camera multitarget tracking data with athletes. The output layer is to save the athlete's trajectory data to the database for motion analysis and key event analysis. Among them, the single-camera multitarget tracking module and the multicamera fusion module form a multicamera multitarget tracking algorithm.

The KCF algorithm, which is mainly used in single-camera multitarget tracking, has fast processing speed and high accuracy and can meet multitarget tracking. However, only through the deep learning algorithm, the RGB information of the image cannot be processed. At the same time, it is difficult to deal with the overlapping and occlusion problems in target tracking. The image retrieval of the KCF algorithm adopts hog feature, and its tracking frame is rectangular. When the shape of the tracking target changes,

the difference between the color and the model becomes larger, which is easy to track failure. In order to improve the accuracy of target detection, the convolutional neural network CNN is used to extract target features and the hog feature used by the KCF algorithm is replaced by the deep convolutional neural network. The improved KCF algorithm adds 5 layers of the convolution layer. The specific process is as follows: using the data sampling of the first frame, the position characteristics of conv3, conv4, and conv5 targets are obtained, and three correlation filters are trained. In the second frame, the conv3, conv4, and conv5 of the target are obtained centered on the prediction result of the first frame. Then, we interpolate the target features, calculate the maximum response point on the confidence score through the filter results of conv5 layer, predict the target position layer by layer according to the order of convolution layer, and finally output the target position prediction results, so as to greatly improve the processing speed. Because it uses the deep learning framework to optimize the features, the target tracking accuracy is improved.

TABLE 2: Information processing speed of the KCF algorithm and improved KCF algorithm.

Algorithm		KCF algorithm	Improved KCF algorithm
Single-target tracking	Video consumption time (s)	24	120
	Time consumed per frame (s)	0.2	1
Single-target tracking	Video consumption time (s)	36	240
	Time consumed per frame (s)	0.3	2

TABLE 3: Single-target tracking accuracy of the KCF algorithm and the improved KCF algorithm.

Tracking frame range (mm)	KCF algorithm (%)	Improved KCF algorithm (%)
20 × 45	75	73
34 × 81	70	67
48 × 106	88	85

TABLE 4: Multitarget tracking accuracy of the KCF algorithm and the improved KCF algorithm.

Tracking frame range (mm)	KCF algorithm (%)	Improved KCF algorithm (%)
20 × 45	60	85
34 × 81	72	92
48 × 106	83	98

3.2. *Experimental Result.* The experimental equipment adopts graphics card NVIDIA 1080, CPU i7-6600, and memory 16g. The KCF algorithm and the improved KCF algorithm are used to test the information processing speed of single-target and multitarget. The video duration is 5 seconds and a total of 120 frames. The test results are shown in Table 2. It can be seen from Table 2 that for single-target tracking, the KCF algorithm consumes 24 seconds, 0.2 seconds per frame, and the improved KCF algorithm consumes 120 seconds, with an average of 1 second per frame. For multitarget tracking, the KCF method consumes 36 seconds, with an average of 0.3 seconds per frame, and the improved KCF method consumes 240 seconds, with an average of 2 seconds per frame.

According to the test results in Table 2, when tracking a single target, the KCF algorithm can track the target faster because of less calculation times and no repeated loading. The improved KCF algorithm belongs to the deep learning algorithm, which requires high computer performance and many calculations at the same time. The target tracking speed is obviously lower than that of the KCF algorithm.

The size of target tracking frame affects the speed of information processing. This paper tests the specific target according to the actual size of the tracking frame. The test video is 5000 frames in total. The tracking target is 5 groups of single players and 5 groups of 2 goalkeepers who are blocked. Select 100 frames of video for small range (20 mm) × 45 mm), medium range (34 mm) × 81 mm), and large range (48 mm) × 106 mm), and compare the target tracking accuracy of the KCF algorithm and the KCF improved algorithm (Table 3). It can be seen from Table 3 that with the increase of the range of target tracking frame, the target tracking accuracy of the two algorithms decreases first and then increases. The target tracking accuracy of the KCF algorithm is still higher than that of the KCF improved algorithm, but the difference is small.

Select 100 frames of video for small range (20 mm) × 45 mm), medium range (34 mm) × 81 mm), and large range (48 mm) × 106 mm), and compare the target tracking accuracy of the KCF algorithm and the KCF improved algorithm (Table 4). It can be seen from Table 3 that with the increase of target tracking frame range, the target tracking accuracy of the two algorithms gradually increases. The target tracking accuracy of the KCF algorithm is far lower than that of the KCF improved algorithm, and the multitarget tracking accuracy of the KCF improved algorithm is higher than 85%.

According to the test results, it can be concluded that with the increase of the tracking frame range, the accuracy of target tracking is improved and multitarget tracking is helpful to improve the antiocclusion ability of the system. This is because when the target tracking frame is large, there is more target feature information in the area. When the target moves, other features are also included in the tracking range, which can effectively solve the problem that the target cannot be tracked due to the rapid movement of players and improve the antiocclusion ability. The accuracy of the KCF algorithm is higher, while the improved KCF algorithm with deep learning has higher accuracy. However, due to objective reasons, the accuracy of target tracking cannot reach 100%.

4. Conclusions

- (1) With the rapid development of the deep learning tracking algorithm, the real-time and accuracy of target tracking have been greatly improved. Taking the video target tracking of football players as the research object, this paper adopts multicamera and multitarget tracking to collect the motion trajectories of multiple players on the court, processes the collected video images, and uses multicameras to obtain

the target feature information. The target features can be corrected by multicameras to ensure the accuracy of target tracking; A multicamera multi-target tracking system is established. The system is divided into input layer, single-camera multitarget tracking module, multicamera data fusion layer, and output layer. The KCF algorithm and the KCF improved algorithm are used to analyze the impact of different target tracking range and target number on the target tracking accuracy of the system, so as to accurately capture the motion trajectory of football players.

- (2) The KCF algorithm and the improved KCF algorithm are used to test the processing speed of the multicamera multitarget tracking system for single-target and multitarget tracking. It is concluded that the KCF algorithm has less calculation times and does not need to be loaded repeatedly and its target tracking speed is significantly higher than that of the improved KCF algorithm. By comparing the target tracking accuracy of the KCF algorithm and the improved KCF algorithm through different target tracking frame sizes, it is concluded that with the increase of the tracking frame range, the target tracking accuracy of the two algorithms is improved. The KCF improved algorithm integrates the algorithm of real-time target detection to enhance the tracking accuracy and antiocclusion ability. When the target tracking frame is large, there is more target feature information in the region. When the target moves, other features are also included in the tracking range, which effectively solves the problem that the target cannot be tracked due to the rapid movement of players and improves the antiocclusion ability. At the same time, the target tracking accuracy of the two algorithms is high.

Data Availability

The figures and tables used to support the findings of this study are included in the article.

Conflicts of Interest

The author declares that there are have no conflicts of interest.

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References

- [1] N. Rusk, "Deep learning," *Nature Methods*, vol. 13, no. 1, p. 35, 2016.
- [2] X. Hao, G. Zhang, and S. Ma, "Deep learning," *International Journal of Semantic Computing*, vol. 10, no. 03, pp. 417–439, 2016.
- [3] T. W. Smith and S. A. Colby, "Teaching for deep learning," *The Clearing House: A Journal of Educational Strategies, Issues and Ideas*, vol. 80, no. 5, pp. 205–210, 2007.
- [4] S. Min, B. Lee, and S. Yoon, "Deep learning in bioinformatics," *Briefings in Bioinformatics*, vol. 18, no. 5, pp. 851–869, 2017.
- [5] K. Yu, L. Jia, Y. Chen, and W. Xu, "Deep learning: yesterday, today, and tomorrow," *Journal of Computer Research and Development*, vol. 50, no. 9, p. 1799, 2013.
- [6] A. C. Mater and M. L. Coote, "Deep learning in chemistry," *Journal of Chemical Information and Modeling*, vol. 59, no. 6, pp. 2545–2559, 2019.
- [7] H. Schulz and S. Behnke, "Deep learning," *KI-Künstliche Intelligenz*, vol. 26, no. 4, pp. 357–363, 2012.
- [8] C. D. Manning, "Computational linguistics and deep learning," *Computational Linguistics*, vol. 41, no. 4, pp. 701–707, 2015.
- [9] X. Rong Li and V. P. Jilkov, "Survey of maneuvering target tracking. Part I. Dynamic models," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 39, no. 4, pp. 1333–1364, 2003.
- [10] S. S. Blackman, "Multiple hypothesis tracking for multiple target tracking," *IEEE Aerospace and Electronic Systems Magazine*, vol. 19, no. 1, pp. 5–18, 2004.
- [11] M. Tahk and J. L. Speyer, "Target tracking problems subject to kinematic constraints," *IEEE Transactions on Automatic Control*, vol. 35, no. 3, pp. 324–326, 1990.
- [12] G. W. Pulford, "Taxonomy of multiple target tracking methods," *IEE Proceedings - Radar, Sonar and Navigation*, vol. 152, no. 5, p. 291, 2005.
- [13] J. Arnold, S. W. Shaw, and H. Pasternack, "Efficient target tracking using dynamic programming," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 29, no. 1, pp. 44–56, 1993.
- [14] J. K. Uhlmann, "Algorithms for multiple-target tracking," *American Scientist*, vol. 80, no. 2, pp. 128–141, 1992.
- [15] D. Smith and S. Singh, "Approaches to multisensor data fusion in target tracking: a survey," *IEEE Transactions on Knowledge and Data Engineering*, vol. 18, no. 12, pp. 1696–1710, 2006.
- [16] S. D. Blostein and H. S. Richardson, "A sequential detection approach to target tracking," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 30, no. 1, pp. 197–212, 1994.
- [17] P. F. Howland, "Target tracking using television-based bistatic radar," *IEE Proceedings - Radar, Sonar and Navigation*, vol. 146, no. 3, p. 166, 1999.
- [18] S. Martínez and F. Bullo, "Optimal sensor placement and motion coordination for target tracking," *Automatica*, vol. 42, no. 4, pp. 661–668, 2006.