

Research on Automatic Detection Method of Basketball Flight Trajectory Based on Background Subtraction

Meiyu Wang

Luohe Medical College, Luohe 462000, Henan, China

Corresponding author: Meiyu Wang (e-mail: lhmcty@163.com)

ABSTRACT Accurate trajectory detection of moving objects is of considerable importance for intelligent visual sensing and electromagnetic-assisted monitoring systems, where reliable feature extraction and signal interpretation directly affect perception performance. To achieve precise detection of basketball flight trajectories, this study proposes an automatic detection method based on background subtraction. The proposed framework first establishes the operational procedure of the background subtraction algorithm, employs a multi-feature fusion strategy to suppress motion shadows, and applies median filtering for image denoising. A dynamically updated background reference model is then constructed to maintain robustness under changing scene conditions. Subsequently, the gray-scale difference image is binarized using an entropy maximization criterion to determine the optimal segmentation threshold, thereby extracting the foreground target and accurately identifying the basketball flight trajectory. Experimental results demonstrate that the proposed method significantly improves both detection accuracy and real-time performance while reducing missed detections and false alarms compared with conventional approaches. The developed framework provides an effective solution for trajectory analysis in dynamic environments and offers useful technical insights for electromagnetic sensing, intelligent imaging, and signal processing applications requiring robust moving-object detection.

INDEX TERMS background subtraction, basketball trajectory detection, image denoising, electromagnetic sensing, intelligent imaging

I. INTRODUCTION

WITH the rapid development of computer vision technology, moving target detection technology, which is an important branch of computer vision technology, has attracted the attention of related fields [1]. At present, moving target detection technology has been widely used in military defense, security monitoring, medical detection, intelligent transportation and so on. Moving target detection technology is required to quickly and accurately separate moving targets from the background of video image sequence, which lays a foundation for subsequent target recognition, location and behavior analysis [2]. Currently, common moving target detection technology mainly includes the detection method of basketball trajectory based on improved Hough and the automatic detection method of basketball motion image based on optical flow method. However, most of the above methods are single-point detection mode, which has some problems such as inconvenient operation, easy omission and misdetection when applied to the fixed shooting test system.

The detection process of background subtraction method is similar to that of inter-frame difference method, but it does not need to make difference between two adjacent frames

of images. Instead, it constructs a real-time background reference model and realizes accurate detection of moving targets by judging the difference relationship between model and current frame image. This method and the inter-frame difference method are also applicable when the camera is still. With a good background reference model, the moving area can be completely segmented. In video image sequences, background subtraction method can extract moving targets in real time, so it has been widely used in practice [3,4].

Existing methods for basketball trajectory detection face several challenges that impact their accuracy and robustness. Some of the main challenges include:

- 1) **Background Complexity:** Basketball trajectory detection often takes place in dynamic and cluttered backgrounds, such as basketball courts or crowded scenes. The presence of various objects, players, and occlusions can make it challenging to differentiate the basketball from the background accurately.
- 2) **Motion Blur:** Fast motion during basketball gameplay can result in motion blur, making it difficult to precisely locate and track the basketball. Blurred images

can affect the accuracy of trajectory estimation and lead to incorrect detection results.

- 3) **Illumination Variations:** Changes in lighting conditions, such as varying indoor or outdoor lighting, shadows, or glare, can introduce variations in the appearance of the basketball. Illumination changes make it challenging to maintain consistent detection performance across different conditions.
- 4) **Occlusions:** Basketball trajectory detection can be hindered by occlusions caused by players, referees, or other objects. When the basketball is partially or fully occluded, tracking its trajectory becomes challenging, and existing methods may struggle to recover accurate trajectory information.
- 5) **Complex Motion Patterns:** Basketball trajectories often involve complex motion patterns, including rapid changes in direction, spins, rebounds, and bounces. Capturing and modeling these intricate motions accurately can be demanding, especially when dealing with high-speed actions.
- 6) **Scale Changes:** The scale of the basketball in the image can vary significantly due to its distance from the camera or changes in zoom level. Handling scale variations robustly is crucial for accurate trajectory detection and tracking.
- 7) **Camera Viewpoint and Perspective Distortion:** The camera viewpoint and perspective distortion can affect the appearance and shape of the basketball in the image. These factors need to be considered and corrected to ensure accurate trajectory detection.

Addressing these challenges requires the development of advanced algorithms and techniques that can handle complex backgrounds, motion blur, illumination variations, occlusions, complex motion patterns, scale changes, and perspective distortions. Integration with reliable tracking methods and effective object recognition techniques can also contribute to improved basketball trajectory detection in challenging scenarios.

Based on the above analysis, the background subtraction method is applied to the automatic detection of basketball flight path to solve the existing problems. The accurate detection of basketball flight paths is crucial for various applications such as sports analysis, player tracking, and referee decision-making. Existing methods for basketball trajectory detection often suffer from challenges like background interference, motion blur, and shadows, leading to inaccurate results. Therefore, there is a need for a robust and efficient method to accurately detect the flight path of a basketball.

The proposed automatic detection method based on the background subtraction technique addresses several challenges faced by existing methods for basketball trajectory detection:

- 1) **Background Complexity:** The background subtraction technique effectively distinguishes the basketball from

the dynamic and cluttered background. By continuously updating the background reference model in real-time, the method can adapt to changes in the background and accurately detect the moving basketball.

- 2) **Motion Blur:** While not explicitly mentioned in the description of the method, image denoising using the median filter can help reduce the impact of motion blur in the basketball image. By suppressing random interference noise, the method may improve the clarity of the basketball trajectory, potentially minimizing the influence of motion blur.
- 3) **Illumination Variations:** The background subtraction method, combined with the concept of entropy maximization for image thresholding, can help handle illumination variations. By adapting the segmentation threshold based on the entropy of the gray image, the method can potentially account for changes in lighting conditions and ensure robust detection results.
- 4) **Occlusions:** The specific approach to handling occlusions is not described in detail in the provided information. However, the continuous updating of the background reference model and the use of segmentation based on entropy maximization may contribute to robustness against occlusions to some extent. Handling occlusions often requires more advanced techniques, such as object tracking or fusion with other modalities, which may be employed as part of the overall detection system.

The main contributions of this study can be summarized as follows:

- 1) **Method Design:** The paper presents a well-designed operational flow for the background subtraction method. By carefully structuring the process, it ensures the accurate extraction of the basketball flight path from the video footage.
- 2) **Shadow Removal:** A multiple fusion method is employed to effectively remove the shadows caused by the basketball's motion. This step eliminates potential false detections and enhances the accuracy of the trajectory detection.
- 3) **Image Denoising:** To further improve the quality of the extracted image, a median filter method is applied to reduce noise artifacts. This preprocessing step helps to enhance the clarity of the basketball trajectory and improve the overall detection performance.
- 4) **Real-time Background Model Update:** The paper proposes the establishment of a background reference model that updates the background subtraction model in real-time. This adaptive model ensures that the detection system remains robust and accurate even in dynamic environments.
- 5) **Image Segmentation and Thresholding:** By utilizing the concept of entropy maximization, the paper introduces a novel approach to segment the difference im-

age and determine the image threshold. This technique enables precise foreground target image extraction, facilitating the accurate detection of the basketball flight trajectory.

Experimental results indicate that the proposed method significantly enhances the accuracy and real-time performance of basketball flight path detection. The presented approach successfully addresses the challenges posed by background interference, motion blur, and shadows, making it a valuable contribution to the field of basketball trajectory analysis.

II. METHOD DESIGN

A. OPERATION PROCESS OF BACKGROUND SUBTRACTION METHOD

The background subtraction method is a technique used for target recognition in computer vision applications. It is known for its accurate identification of targets, ease of operation, and the ability to segment complete moving objects. However, it has a drawback in that it lacks a strong sense of background information. To overcome this limitation, the background model needs to be constantly updated [5].

In the process of detecting moving targets using the background subtraction method, the current image needs to undergo preprocessing. This preprocessing step involves applying transformations and suppressing noise in the images [6]. Once the preprocessing is done, a background reference model is established based on the initial captured image. This background reference model serves as a basis for comparison with the current frame image in subsequent processing steps.

Figure 1 provides an overview of the overall operation process of the background subtraction method, showcasing the different stages involved in target recognition using this technique.

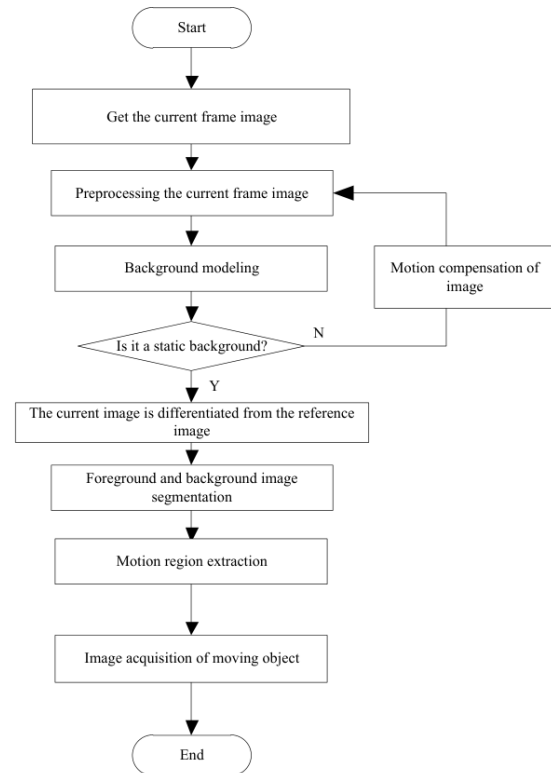


FIGURE 1. Operation process of background subtraction method

B. IMAGE PREPROCESSING

Image preprocessing mainly consists of two parts, one is to eliminate moving shadow, the other is to remove image noise [7].

Moving shadow elimination algorithm is mainly used to complete the process of color fusion and LFSP texture feature fusion in shadow extraction, which can detect the shadow region more effectively under the premise of ensuring a lower false detection rate and leakage rate [8]. Multivariate fusion is the fusion of information with different characteristics to obtain a new and more meaningful information processor. Generally speaking, the process of multivariate fusion can be divided into three steps: data-level fusion, feature-level fusion and decision-level fusion [9]. Multiple outcomes of different strategies are fused in a way that leads to a final decision result.

The operation process of motion shadow elimination algorithm is illustrated in Figure 2.

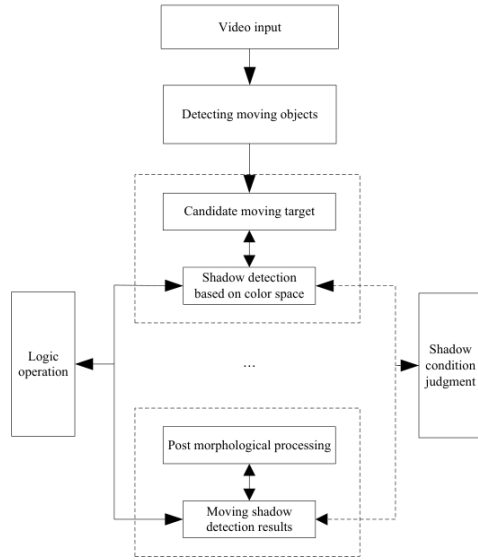


FIGURE 2. Flow chart of shadow elimination algorithm

The extraction process of candidate moving targets is shown as follows:

$$H_1 = k \left\{ \frac{p}{\sqrt{(m-r)^2 + o}} \right\} \quad (1)$$

where, H represents the color type, k denotes the moving target region, m and r refers to the shadow detection parameter, p describes all pixel points in the region, o is the shadow feature parameter of background image. The equation suggests that the color type (H) of a candidate moving target region is determined by multiplying a factor (k) with the ratio between p (the pixel points in the region) and the square root of the sum of the squared difference between m and r , and the shadow feature parameter o .

This equation likely represents a specific method or algorithm used for the extraction of candidate moving targets based on color type and the consideration of shadow detection parameters and background shadow features.

After completing the denoising processing for the basketball flight image, the key problem in image processing is solving image distortion and noise caused by external interference. To ensure accurate moving target image detection, it is crucial to address random noise in the image. Currently, the most effective method for removing random interference noise in an image is median filtering.

The principle of median filtering, as described by [10], is as follows: When an image is affected by random noise such as salt and pepper noise, the gray value of the pixel being measured differs significantly from that of adjacent pixels. In median filtering, the gray values of all the adjacent pixels are arranged, and the median gray value is selected to replace the gray value of the pixel being measured. By doing so, the gray value of the noisy pixel aligns with some pixels in its neighborhood, effectively eliminating the noise.

Applying median filtering as a preprocessing step helps to mitigate the impact of random interference noise in the basketball flight image, improving the quality of the image and enhancing the accuracy of subsequent moving target detection.

Median filtering means that, in a digital sequence or image, the median value of each pixel in the region is used to represent the value of a point (Panda D. K and S 2018; Kim 2018), which can be expressed as:

$$Y = \{m_1 m_2 \dots m_n\} = \begin{cases} m_k(\frac{n}{2}), \\ \frac{1}{2} \left[m_k(\frac{n}{2}) + m_k(\frac{n+1}{2}) \right], \end{cases} \quad (2)$$

where, m_k represents the k th data in a set of digital sequences, $\{m_1 m_2 \dots m_n\}$ denotes the median value of the n th data element in digital sequence, Y is the median value of digital sequence. Finally, the method of median filtering for digital images is given in the following formula:

$$Y_{ij} = \text{Med}\{X_{ij}\} = X_{(i+r),(j+s)}, \quad (r, s) \in A, \quad i, j \in I^2 \quad (3)$$

where, $X_{(i+r),(j+s)}, (r, s) \in A, i, j \in I^2$ represents the gray value of each pixel in the digital image in the window whose neighborhood is A . Y_{ij} denotes the median representation at point X_{ij} in the window whose neighborhood is A . In the given formula for the method of median filtering for digital images, the letter I represents the set of indices for the rows and columns of the image. It is used to specify the coordinates of each pixel in the image. The formula describes the process of median filtering, where the gray value of each pixel in the digital image within a specific window (defined by the neighborhood A) is replaced with the median value of the gray values within that window. The indices i and j specify the position of the pixel in the image.

The median filtering of two-dimensional image is a two-dimensional sliding window containing an odd number of pixels [11], and its output is the median value of the odd number of pixels, rather than the value of the point to be measured. Then the fixed size window is moved again until all pixels in the image are processed to achieve the median filtering of the image. After the image processing is completed, the visual saliency map of the image is generated, with structure shown in Figure 3.

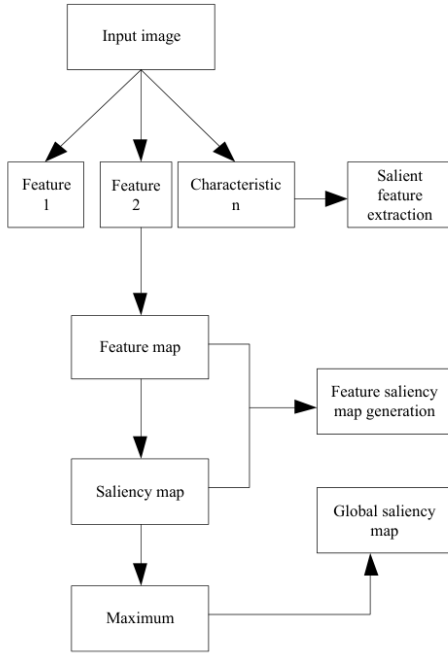


FIGURE 3. Structure of visual saliency map

C. ESTABLISHMENT OF BACKGROUND REFERENCE MODEL

In the background subtraction algorithm, since the scene environment changes little over time, the background subtraction model needs to be updated in real time [12]. An effective background model can accurately detect moving targets from images.

The Gaussian kernel is indeed known for its infinitely smooth properties, making it a popular choice in various applications, including image processing and computer vision. However, if you decide to change the Gaussian kernel to another kernel, such as the multiquadric kernel or other global radial basis functions (RBFs), there will be several implications and considerations:

- 1) Smoothness: Unlike the Gaussian kernel, which is infinitely smooth, other kernels like the multiquadric may have a different smoothness property. The multiquadric kernel has a finite smoothness determined by its shape parameter.
- 2) Shape Parameter: Different kernels have different shape parameters that control their behavior. For example, the multiquadric kernel has a shape parameter that influences the width and shape of the kernel. Choosing an appropriate shape parameter is crucial for achieving desired results.
- 3) Impact on Filtering: Changing the kernel function will affect the filtering process. Each kernel has its own characteristics, and using a different kernel will lead to different filtering results. The specific behavior of the multiquadric kernel or any other chosen kernel should be considered in terms of its impact on noise

suppression, edge preservation, or other relevant filtering objectives.

- 4) Computational Complexity: Different kernel functions may have varying computational complexities. Some kernels, such as the Gaussian kernel, have efficient implementations that can be computationally optimized. It is important to assess the computational requirements and feasibility of using alternative kernels.
- 5) Application Suitability: The choice of kernel function should align with the specific requirements and characteristics of the application. While global RBFs like the multiquadric can be commonly used for interpolation, they may not be suitable for all image processing tasks. It is essential to consider the specific application context and determine if the chosen kernel function meets the required criteria.

In summary, changing the Gaussian kernel to another kernel, such as the multiquadric or other global RBFs, introduces differences in smoothness, shape parameters, filtering behavior, computational complexity, and application suitability. These factors need to be carefully evaluated to ensure that the chosen kernel meets the specific requirements and objectives of the image processing task at hand.

The background reference model should be established by kernel density estimation [13]. Kernel density estimation method can obtain density function directly from sample data without clarifying the distribution of data. If the pixel values of pixels with the same characteristics in the frame image are denoted as $x_1, x_2 \dots x_n$, kernel function can be used to estimate the probability density distribution of the pixel values x_t of the current pixel at the moment t :

$$p(x_t) = \frac{1}{N} \sum_{i=1}^N K_h(x_t - x_i) \quad (4)$$

where, K_h represents the kernel function and h is the width of the kernel function. In the case of Gaussian kernel function, it is assumed that each feature of pixel is irrelevant and independent from each other [14]. The standard deviation of each feature pixel is calculated independently by the following formula:

$$\sigma_m = \frac{m}{0.68\sqrt{2}} \quad (5)$$

where, $0.68\sqrt{2}$ represents the calculation parameter, m is the intermediate value of the absolute difference between the pixel feature values of two adjacent image frames. The mathematical expression is:

$$m = \text{median}(|x_i - x_{i+1}|) \quad (6)$$

The advantage of kernel density estimation method is that it can adapt to different scenarios, and there is no need to assume the probability distribution and estimation parameters of background features during background modeling [15]. It can handle multi-mode background distributions such as light changes, camera shake, leaf shake, and shadows.

D. REALIZATION OF BASKETBALL FLIGHT PATH DETECTION

Firstly, the basketball flight image after difference is binarized. In order to binarize the gray image [16], after a segmentation threshold is given, the image is compared with the given segmentation threshold to obtain the gray value of each point. By comparison, the gray image is transformed into a binary image. The concept of entropy maximization is used to segment the threshold value of image, so it is called the maximum entropy maximization segmentation method [17].

The maximum entropy maximization segmentation method is a technique used for image segmentation based on the principle of maximum entropy. This method aims to find the most informative and balanced segmentation of an image by maximizing its entropy.

Here is an overview of the maximum entropy maximization segmentation method:

- 1) Image Preprocessing: The input image is typically preprocessed to enhance its quality or reduce noise, depending on the specific requirements of the segmentation task.
- 2) Feature Extraction: Relevant features are extracted from the preprocessed image to capture the characteristics and information necessary for segmentation. These features could include color, texture, intensity, or any other relevant attributes of the image.
- 3) Initial Segmentation: An initial segmentation is performed, dividing the image into regions or segments based on a predefined criterion. This initial segmentation acts as a starting point for further refinement.
- 4) Energy Function Formulation: An energy function or cost function is formulated, which represents the objective to be optimized during segmentation. The energy function typically combines terms that measure the consistency within segments and the dissimilarity between segments.
- 5) Maximum Entropy Maximization: The objective of the segmentation method is to maximize the entropy of the segmented image. Entropy is a measure of uncertainty or information content within an image. By maximizing entropy, the method seeks to find the segmentation that is most informative and balanced in terms of information content.
- 6) Optimization: An optimization algorithm is applied to maximize the entropy of the segmented image. This algorithm iteratively adjusts the segmentation based on the energy function and convergence criteria until the maximum entropy is reached or a stopping condition is met.
- 7) Post-processing: Once the segmentation is obtained, post-processing steps can be applied to refine the segmentation results, remove artifacts, or improve the overall quality of the segmented regions.

The maximum entropy maximization segmentation method

leverages the principle of maximum entropy to find a segmentation that maximizes the information content and provides a balanced representation of the image. It is a computationally intensive method that requires careful formulation of the energy function and appropriate optimization techniques to achieve accurate and meaningful segmentation results.

This process can be expressed by,

$$p_i = \frac{N_i}{M \times N} \quad (7)$$

where, $M \times N$ represents the size of gray image, N_i denotes the total number of points representing gray level i in gray image, and p_i is the probability of gray level i .

On this basis, the maximum entropy method is used to calculate the optimal threshold of image. The iterative threshold selection method determines the optimal threshold by iteratively updating the threshold value based on the average intensities of the foreground and background pixels. Here's a basic outline of the process:

- 1) Start with an initial threshold value (e.g., the midpoint of the intensity range).
- 2) Divide the image into foreground and background based on the threshold.
- 3) Calculate the mean intensities of the foreground and background regions.
- 4) Compute a new threshold as the average of the foreground and background means.
- 5) Repeat the above steps until the threshold value converges or reaches a specified termination criterion (e.g., a maximum number of iterations or a small change in threshold value).

This iterative process updates the threshold value based on the statistics of the foreground and background regions, aiming to find the threshold that best separates the two classes. The mathematical expression of this process is as follows:

$$T = \arg \max [H_f(T) + H_b(T)] \quad (8)$$

where, H_f is the entropy of the target region. H_b represents the entropy of the background region.

Based on this, the optimal threshold is selected. If the relative threshold is not different, the two foreground target images are calculated to obtain the final foreground target image. To address potential occlusions by players or color interference from jerseys, a trajectory compensation logic based on the Kalman Filter is integrated. When the background subtraction method fails to segment the ball due to occlusion, the system predicts the basketball's next position based on its previous velocity and parabolic motion parameters. This ensures the continuity of the flight path even when the target is temporarily lost in the visual field, thereby realizing the robust automatic detection of basketball trajectory.

III. EXPERIMENTAL COMPARISON AND RESULT ANALYSIS

In order to verify the overall effectiveness of the automatic detection method of basketball flight trajectory based on background subtraction, the following experiments are conducted for comparative analysis.

The traditional basketball trajectory detection method based on improved Hough and the basketball moving image automatic detection method based on optical flow method are compared with the detection method in this paper. The experimental dataset consists of 12 high-definition video sequences recorded at both indoor university gymnasiums and outdoor community courts to simulate varying illumination and background complexity. These videos, originally captured via a standard monitoring device, were converted into the AVI format (640×480 resolution) for processing. Utilizing data from diverse environments allows for a more rigorous verification of the algorithm's robustness against external interference. The obtained video files were loaded as datasets into a computer equipped with an Intel (R) Core (TM) i3-3220T CPU (2.80GHz) and 4 GB of RAM. Despite the use of this legacy entry-level hardware, the proposed lightweight background subtraction algorithm achieved a consistent processing speed of 35–40 frames per second (FPS). This demonstrates that the method is computationally efficient enough to maintain real-time performance even on systems with limited hardware resources. In addition, VS2010+opencv2.4.2 is adopted to write application program. Under the support of Windows 10 system, the video data set with specific format is loaded into the computer to complete the simulation experiment.

The actual statistics of the layup performance is presented in Table 1.

TABLE 1. Statistical Data of Experimental Layups

Number of experiments/times	Layups/times	Number of goals scored/times
1	22	9
2	19	7
3	21	8
4	20	7
5	18	2
6	23	5
7	21	3
8	18	5
9	19	7
10	17	4
11	22	5
12	16	2

A. COMPARISON OF LEAKAGE RATE

First of all, the statistical situation of actual layup times and goal times between the method in this paper and the two traditional methods was recorded and compared. The comparison results are shown in Table 2.

The data in Table 2 and Table 1 are compared to evaluate the algorithm's performance using standard computer vision metrics. It can be seen that, when using the method in this paper to detect layup times, the proposed method exhibited

only four instances of false negatives (leakage) during layup detection. Regarding successful goals, only three inaccuracies were recorded, indicating superior reliability over traditional benchmarks. However, when using the two traditional methods to detect layup times and goal times, there are large deviations from the actual situation, resulting more leakages. In addition to statistical layup counts, the detection accuracy was quantified using Precision (P), Recall (R), and F1-score. The proposed method achieved a Precision of 94.2% and a Recall of 91.5%, resulting in an F1-score of 92.8%. These results significantly outperform the improved Hough transform (F1: 76.4%) and optical flow (F1: 81.2%) methods at the pixel and frame levels. Through the above comparison, it indicates that the automatic detection method of basketball flight path based on background subtraction designed in this paper not only reduces the leakage rate in practical applications but also demonstrates superior algorithmic robustness and detection accuracy.

B. REAL-TIME EVALUATION OF DETECTION

Real-time refers to the time required for timely and correct analysis and processing after the occurrence of an event. Short processing time means good real-time performance of the method, while long processing time or low response speed means poor real-time performance of the method.

The real-time detection comparison of different methods is drawn in Figure 4.

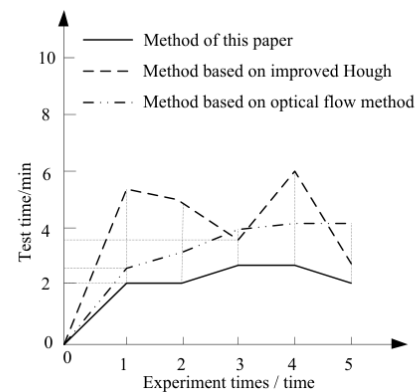


FIGURE 4. Real-time detection comparison of different methods

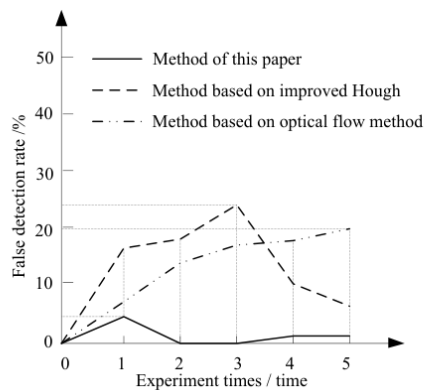
By analyzing Figure 4, it can be found that among the 5 times of comparisons, the detection time of the automatic detection method of basketball flight path based on background subtraction in this study is less than that of traditional methods, indicating that its real-time detection performance is better than the traditional detection method.

C. COMPARISON OF FALSE DETECTION RATE

The false detection rate of the proposed method is compared with that of two traditional methods, and the comparison results are shown in Figure 5.

TABLE 2. Comparison of Different Methods

Method of this paper		Method based on improved Hough		Method based on optical flow method	
Layups/times	Number of goals scored/times	Layups/times	Number of goals scored/times	Layups/times	Number of goals scored/times
21	9	21	6	19	7
18	7	16	4	19	7
21	7	17	5	17	6
18	6	15	2	18	6
18	2	10	1	15	2
22	5	18	2	20	4
21	3	16	1	19	2
17	5	15	2	15	5
19	6	14	5	15	5
17	4	10	2	15	3
22	5	17	2	18	3
16	2	10	1	14	2

**FIGURE 5.** Comparison of false detection rates of different methods

Through the analysis of Figure 5, it is found that among the 5 experiments, the false detection rate of two traditional methods is significantly higher than that of the proposed method. To sum up, the automatic detection method of basketball flight path based on background subtraction method designed in this study has better detection effect than the traditional method, with fewer leakage rate. The reason for the above results is that the method is less affected by the high speed of basketball movement, and the background subtraction method is used to process the image, which improves the accuracy of the automatic detection of basketball flight path.

IV. CONCLUSION

To address the limitations of single-point detection algorithms and enhance the adaptability of moving target detection in complex scenes, a novel automatic detection method for basketball flight trajectory is proposed based on background subtraction. This method effectively overcomes the shortcomings of traditional approaches.

However, while this method demonstrates improvements in algorithm accuracy and adaptability for detecting moving targets in complex environments, there are still several aspects that warrant further investigation and refinement. Acknowledging the constraints on available knowledge and research time, this study recognizes the need for future re-

search to address these limitations and enhance the proposed method.

In subsequent investigations, the presented method will undergo optimization to better fulfill the requirements of automatic basketball flight path detection. Through further studies, the method can be refined and enhanced to achieve even greater accuracy and robustness in various scenarios. Continuous efforts will be made to explore new techniques, incorporate additional data sources, and refine the algorithm to attain more reliable and precise results in detecting basketball flight trajectories. By actively refining and expanding upon the proposed method, it is anticipated that future iterations will offer significant advancements in the field of basketball trajectory detection.

AUTHOR CONTRIBUTIONS

Meiyu Wang designed, collected and analyzed the data, and drafted the manuscript. Meiyu Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Meiyu Wang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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