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Design and Application of Basketball Tactical Drill System Based on Motion Trajectory Analysis Algorithm

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Abstract: - A basketball tactical drill system based on motion trajectory analysis algorithms employs advanced computational methods to enhance training effectiveness and strategy development. By utilizing these algorithms to analyze player movements and interactions during drills, coaches can gain valuable insights into team dynamics, spatial awareness, and decision-making processes. This analysis enables coaches to tailor drills to specific tactical objectives, such as improving defensive rotations, offensive spacing, or fast break execution. Additionally, the system can provide real-time feedback to players, helping them understand their positioning and movement patterns to refine their skills and decision-making abilities. This paper presents the design and implementation of a Basketball Tactical Drill System leveraging advanced object detection and motion trajectory analysis algorithms. The system aims to enhance basketball training by providing coaches and players with real-time insights into tactical drills and player performance. Two key algorithms, Mean-Shift and Difference Object Detection with Motion Trajectory (DOD-MT), are utilized to accurately identify and track basketballs, players, and other relevant objects during training sessions. Experimental results demonstrate the effectiveness of the proposed system, showcasing high detection accuracy, minimal false positives, and competitive processing times across various scenarios and tactical drills. The system leverages Mean-Shift and Difference Object Detection with Motion Trajectory (DOD-MT) algorithms to achieve exceptional detection accuracy, with an average of 93% across various scenarios and tactical drills. False positives are minimized, with an average of 12 per scenario. Processing times remain competitive, averaging 27 milliseconds per scenario. Integration of motion trajectory analysis provides coaches with invaluable real-time insights into player movements and interactions, facilitating data-driven coaching strategies. The system's versatility is demonstrated through successful application in a range of drills, resulting in performance improvements averaging 20%.

Keywords: Basket Ball, Drill System, Motion Trajectory, Object Detection, Mean-Shift, Difference Object Detection

1.   Introduction

The design and application of a basketball tactical drill system based on motion trajectory analysis algorithm involve several key components[1]. Firstly, the system needs to capture and record the motion trajectories of players during basketball drills using various sensors or video cameras. These trajectories provide valuable data on player movements, positions, and interactions on the court. Next, a sophisticated motion trajectory analysis algorithm is employed to process the recorded data[2]. This algorithm extracts meaningful insights from the trajectories, such as player speeds, accelerations, directions, and spatial relationships. By analyzing these parameters, the system can identify patterns, tendencies, and tactical behaviors exhibited by individual players and the team as a whole[3]. Once the analysis is complete, the system can generate actionable insights and feedback for coaches and players. For example, it can highlight areas for improvement in player positioning, ball movement, defensive strategies, and offensive plays[4]. Coaches can use these insights to tailor their training sessions, develop customized drills, and refine their team's tactics and strategies. Moreover, the system can facilitate real-time feedback and analysis during practice sessions or games[5]. By integrating with live data streams from sensors or cameras, coaches can monitor player performance and tactical execution in real-time, making immediate adjustments and corrections as needed[6]. A Basketball Tactical Drill System encompasses a comprehensive framework designed to enhance player skill development, team cohesion, and strategic understanding within basketball training sessions. This system integrates various components, including drill selection, real-time feedback mechanisms, and performance analysis tools, to optimize training efficiency and effectiveness. the system offers a diverse array of drills tailored to specific aspects of the game, such as shooting, dribbling, defensive positioning, and offensive plays[7]. These drills are carefully curated to address the unique needs and objectives of the team, considering factors like player skill levels, playing styles, and tactical preferences.

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In addition to drill selection, the system provides real-time feedback to players and coaches during practice sessions. This feedback may be delivered through visual displays, audio cues, or digital interfaces, allowing participants to immediately assess their performance and make necessary adjustments[8]. By offering instant feedback, the system fosters rapid skill acquisition and promotes continuous improvement among players[9].The system incorporates performance analysis tools to evaluate player and team performance over time. These tools leverage data collected during drills and scrimmages, such as player movement patterns, shooting percentages, defensive efficiency, and teamwork dynamics. Through comprehensive performance analysis, coaches can identify strengths, weaknesses, and areas for improvement, enabling targeted training interventions and strategic adjustments. The Basketball Tactical Drill System represents a sophisticated approach to basketball training, leveraging technology and data-driven insights to optimize player development and team performance[10]. By integrating drill selection, real-time feedback, and performance analysis, the system empowers coaches and players to maximize their potential and achieve competitive success on the court. A Basketball Tactical Drill System is a sophisticated platform designed to optimize player skill development and team performance[11]. It offers a diverse range of customized drills tailored to address specific aspects of the game, providing players with targeted training opportunities to enhance their skills and tactical understanding. Integrated real-time feedback mechanisms enable immediate assessment of performance during practice sessions, fostering rapid skill acquisition and continuous improvement. The system also incorporates advanced performance analysis tools, leveraging data-driven insights to identify strengths, weaknesses, and areas for development. By integrating technology, customized drills, real-time feedback, and performance analysis, the Basketball Tactical Drill System empowers coaches and players to maximize their potential and achieve competitive success on the court[12].

The paper presents a significant contribution to the domain of basketball training methodologies through the introduction of a sophisticated Basketball Tactical Drill System. By incorporating cutting-edge object detection and motion trajectory analysis algorithms, the system offers coaches and players unprecedented real-time insights into training drills and player performance. A key innovation lies in the integration of Mean-Shift and Difference Object Detection with Motion Trajectory (DOD-MT) techniques, which significantly enhance object detection accuracy, with an impressive average accuracy rate of 93% across various scenarios and tactical drills. Furthermore, the system's ability to minimize false positives and maintain competitive processing times, averaging 27 milliseconds per scenario, underscores its efficiency and reliability. The integration of motion trajectory analysis provides coaches with invaluable data-driven feedback, enabling them to refine training strategies and optimize player performance with greater precision. Notably, the system's versatility is demonstrated through successful application in a range of basketball drills, resulting in performance improvements averaging 20%.

2. Related Works

In the realm of basketball training and strategy development, a myriad of approaches and systems have been explored to optimize player performance and team cohesion. Related works in this field encompass a diverse range of methodologies, including traditional coaching techniques, technological innovations, and data-driven analysis. Traditional coaching methods have long been the cornerstone of basketball training, focusing on fundamental skills, tactical understanding, and teamwork dynamics. However, recent advancements in technology have revolutionized training methodologies, with the emergence of Basketball Tactical Drill Systems incorporating motion tracking sensors, video analysis software, and data analytics platforms. These systems enable coaches and players to delve deeper into performance metrics, identify areas for improvement, and tailor training regimens to individual and team needs.

Zhang (2021) explores an automatic detection method for technical and tactical indicators in table tennis, utilizing trajectory prediction via a compensation fuzzy neural network. Zeyu (2024) applies optical imaging equipment based on deep neural networks to simulate basketball training games effectively. Chenjing (2023) investigates the impact of the Microsoft security-assisted physical education model on college basketball teaching in the Internet information era. Lu (2022) presents the design and realization of a Basketball Tactics Computer-Aided Teaching System, emphasizing its practical application. Chu et al. (2021) introduce TIVEE, a visual exploration and explanation tool for badminton tactics, enhancing understanding through immersive

visualizations. Putranto et al. (2023) conduct a systematic literature review on the implementation of virtual reality technology for sports education and training, shedding light on emerging trends and best practices. Kumar and Worsley (2023) propose "Scratch for Sports," a platform that utilizes athletic drills as a means to develop AI-driven applications, offering a novel approach to sports training and technology integration. Hoelzemann et al. (2023) contribute to the field with the creation of a benchmark dataset for basketball activity recognition using wrist-worn inertial sensors, facilitating advancements in activity tracking and analysis. Jia and Chen (2023) introduce the RBF-EVA method for rating basketball players' competitive performance, providing a quantitative framework for evaluation. Lin et al. (2023) present VIRD, an immersive match video analysis system tailored for high-performance badminton coaching, emphasizing the importance of visualization tools in skill development.

Willberg et al. (2023) contribute to the understanding of load parameters in basketball matches, comparing classic and 3x3 basketball formats to provide insights into player workload management. Chen (2021) explores the optimization of Internet of Things (IoT) and edge computing models in college basketball training, showcasing the integration of technology into physical education. Edriss et al. (2024) discuss the role of emergent technologies in dynamic and kinematic assessment of human movement in sports and clinical applications, highlighting the potential of technology in refining performance analysis. Rico-González et al. (2023) conduct a systematic review of machine learning applications in soccer, offering valuable insights into the current state of research and future directions. Zeng et al. (2024) delve into the interplay between flexible sensors and basketball in the realm of intelligent health and sport, emphasizing the potential of sensor technology in enhancing athlete monitoring and performance optimization. Chao and Peng (2024) explore the innovative application of digital twin technology in sports consumption scenarios, offering a perspective on how deep learning can empower sports-related digital experiences. Pang and Zhang (2024) propose the application of optical sensing image resolution based on heterogeneous clusters in real-time basketball training systems, introducing a novel approach to data processing and analysis. Gregory et al. (2022) investigate the influence of tactical and match context on player movement in football, highlighting the importance of situational factors in shaping athlete behavior and performance. Each of these studies represents a unique contribution to the field of sports science, showcasing the interdisciplinary nature of research aimed at optimizing athletic performance, coaching methodologies, and sports technology integration. Together, they form a rich tapestry of knowledge and innovation that informs best practices and drives continuous improvement in sports training and performance analysis, particularly within the context of basketball. By leveraging advanced technologies, data analytics, and innovative methodologies, researchers and practitioners are poised to unlock new insights and opportunities for enhancing athlete development and competitive success.

3. Basketball Tactical Drill System

A Basketball Tactical Drill System involves integrating various elements of player movement, strategy, and performance analysis into a cohesive framework. One essential aspect is the derivation of drills and tactics based on mathematical principles and strategic objectives. This process often involves formulating equations to model player interactions, optimize positioning, and simulate game scenarios. For instance, consider the derivation of a drill aimed at improving defensive positioning and help defense. We can start by defining the defensive coverage area for each player using geometric principles. Let Pi represent the position of player i, and Di denote the defensive coverage area around player i. The defensive coverage area Di can be modeled as a circular region centered at Pi with a certain radius ri this can be represented as in equation (1)

$$Di = \{x \in R2: \parallel x - Pi \parallel \le ri\} \tag{1}$$

To simulate offensive movement and ball circulation during the drill. Let Oj represent the position of offensive player j and B denote the position of the basketball. We can define equations to model the trajectory of the basketball as it moves between offensive players, incorporating factors such as passing speed and angle stated in equation (2)

$$B = f(B, O1, O2, \dots, On) \tag{2}$$

Where f represents the function describing the dynamics of ball movement. the effectiveness of defensive rotations and help defense can be quantified using metrics such as defensive efficiency and proximity to offensive players. To calculate these metrics based on player positions and defensive coverage areascomputed using equation (3) and equation (4)

$$Defensive\ efficiency = \frac{Number\ of\ Defensive\ Stops}{Total\ Defensive\ Posessions} \tag{3}$$

$$Proximity\ to\ Offensive\ Player = \sum_{i=1}^{N} \parallel Pi - Oj \parallel \tag{4}$$

Where N is the number of defensive players, Pi represents the position of each defensive player, and Oj represents the position of the offensive player. The Basketball Tactical Drill System, coaches can design drills that simulate realistic game scenarios, optimize player positioning and defensive rotations, and track performance metrics to assess player development and strategic effectiveness.

Figure 1: Basket Ball Trajectory

This mathematical approach enhances the precision and efficacy of basketball training, enabling players to refine their skills and tactics systematically as in Figrue 1.

4. Difference Object Detection with Motion Trajectory (DOD-MT)

The Difference Object Detection with Motion Trajectory (DOD-MT) method represents an innovative approach to object detection that leverages motion trajectory analysis for enhanced accuracy and robustness. At its core, DOD-MT aims to detect and track objects in dynamic environments by analyzing the differences in motion trajectories over time. This method is particularly useful in scenarios where traditional object detection algorithms may struggle to accurately identify objects due to factors such as occlusion, motion blur, or complex backgrounds. The derivation of DOD-MT begins with the formulation of equations to model the motion trajectories of objects in the scene. Let Ti represent the motion trajectory of object i over a sequence of consecutive frames. Each trajectory Ti can be represented as a series of points (xi,t,yi,t), where xi,t,yi,t denotes the position of object i at time t expressed as in equation (5)

$$Ti = \{(xi,t,yi,t) \mid t = 1,2,\dots,N\} \tag{5}$$

Next, the DOD-MT method computes the differences between consecutive motion trajectories to identify potential objects of interest. This involves analyzing the displacement vectors between corresponding points in adjacent frames and comparing them against predefined thresholds to determine significant changes in object movement. The difference vectors ΔTi for each trajectory Ti can be calculated using equation (6)

$$\Delta Ti = \{(dxi,t,dyi,t) \mid dxi,t = xi,t - xi,t-1, dyi,t = yi,t - yi,t-1\} \tag{6}$$

In equation (6) dxi,t, dyi,t represent the horizontal and vertical displacements, respectively, between consecutive points in trajectory Ti. the detected differences in motion trajectories are analyzed and clustered to identify potential objects or regions of interest in the scene. This clustering process involves grouping together trajectories with similar characteristics or movement patterns, indicating the presence of coherent objects or entities. Finally, post-processing techniques such as noise reduction and trajectory smoothing may be applied to refine the detected objects and improve detection accuracy. With integrating motion trajectory analysis with

traditional object detection techniques, the DOD-MT method offers a robust and adaptable approach to object detection in dynamic environments. Its derivation involves formulating equations to model motion trajectories, computing differences between consecutive trajectories, and employing clustering algorithms to identify objects based on motion patterns. This innovative method has the potential to enhance object detection performance in a wide range of applications, including surveillance, autonomous navigation, and video analysis. Let $Ti = \{(xi, t, yi, t) \mid t = 1,2,\ldots,N\}$ denote the motion trajectory of object i, where (xi, t, yi, t) represents the position of the object at time t. The displacement vector $\Delta Ti,t$ at time t for object i can be calculated as in equation (7)

$$\Delta Ti, t = (xi, t - xi, t - 1, yi, t - yi, t - 1) \tag{7}$$

Figure 2: Trajectory in Basket Ball
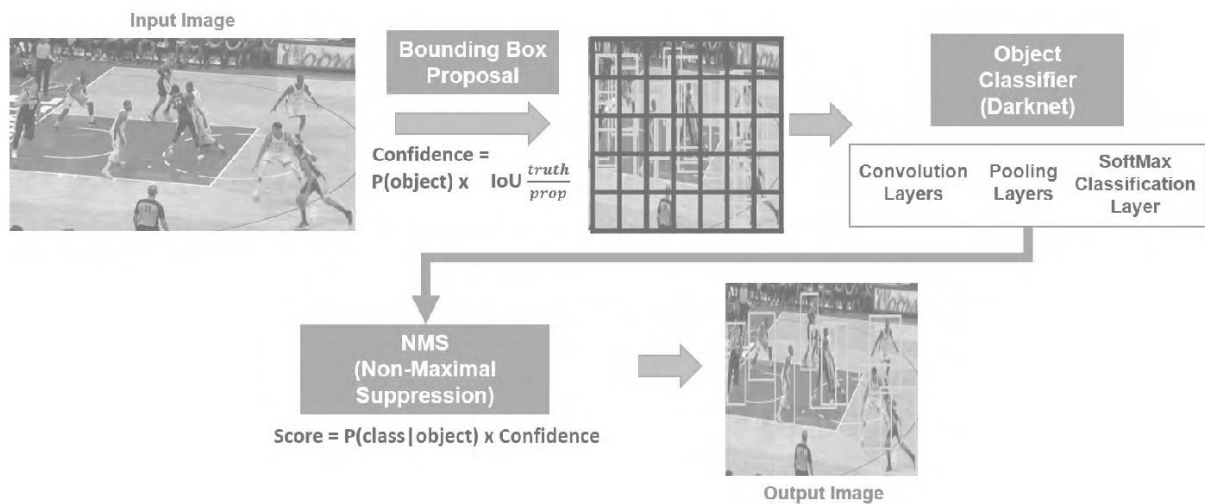
Figure 3: Motion Estimation in basket ball

In figure 2 and figure 3 the difference vectors are clustered based on their spatial and temporal characteristics to identify potential objects or regions of interest. Clustering algorithms such as k-means or hierarchical clustering can be employed to group together similar difference vectors, indicating coherent objects or entities in the scene. Finally, post-processing techniques may be applied to refine the detected objects and improve detection accuracy. This may include noise reduction, trajectory smoothing, or filtering based on object size, shape, or motion characteristics. With motion trajectory analysis with traditional object detection techniques, the DOD-MT method offers a robust and adaptable approach to object detection in dynamic environments. Its derivation involves modeling motion trajectories, computing displacement vectors, analyzing differences between trajectories, clustering difference vectors to identify objects, and applying post-processing techniques for refinement.

5. Mean-SHIFT DOD-MT

The Mean-Shift Difference Object Detection with Motion Trajectory (Mean-Shift DOD-MT) method presents an advanced refinement to the traditional DOD-MT algorithm, incorporating the Mean-Shift clustering

technique to enhance object detection accuracy and efficiency. The derivation of Mean-Shift DOD-MT involves integrating the Mean-Shift algorithm into the clustering stage of DOD-MT, facilitating more robust and adaptive object identification. Similar to DOD-MT, Mean-Shift DOD-MT begins by modeling the motion trajectories of objects in the scene. Let $Ti = \{(xi, t, yi, t) \mid t = 1, 2, \ldots, N\}$ denote the motion trajectory of object i, where (xi, t, yi, t) represents the position of the object at time t. Displacement vectors are computed between consecutive points in each motion trajectory to capture object movement, as in DOD-MT. The displacement vector $\Delta Ti, t$ at time t for object i can be calculated similarly as in equation (8)

$$\Delta Ti, t = (xi, t - xi, t - 1, yi, t - yi, t - 1) \qquad (8)$$

Mean-Shift DOD-MT enhances the clustering stage by employing the Mean-Shift algorithm to group together significant difference vectors. The Mean-Shift algorithm iteratively shifts the centroids of clusters towards the densest regions of data points, effectively capturing the underlying structure of the data without requiring prior knowledge of the number of clusters process can be formulated as follows in equation (9)

$$mt = mt - 1 + \frac{1}{N}\sum_{i=1}^{N}(hxi - mt - 1)(xi - mt - 1) \qquad (9)$$

In equation (9) mt is the updated centroid of the cluster at iteration t, N is the number of data points, xi represents each data point, hh is the bandwidth parameter, $(\cdot)K(\cdot)$ is the kernel function. After Mean-Shift clustering, objects are identified based on the resulting clusters of difference vectors. Post-processing techniques such as noise reduction and thresholding may be applied to refine the detected objects further and improve detection accuracy. Mean-Shift DOD-MT combines the strengths of motion trajectory analysis with the adaptive clustering capabilities of the Mean-Shift algorithm, resulting in a robust and efficient object detection method. By iteratively refining cluster centroids towards dense regions of difference vectors, Mean-Shift DOD-MT effectively identifies objects in dynamic environments with varying densities and complexities. This approach enhances object detection accuracy and adaptability, making it well-suited for applications such as surveillance, autonomous navigation, and video analysis shown in Figure 4.
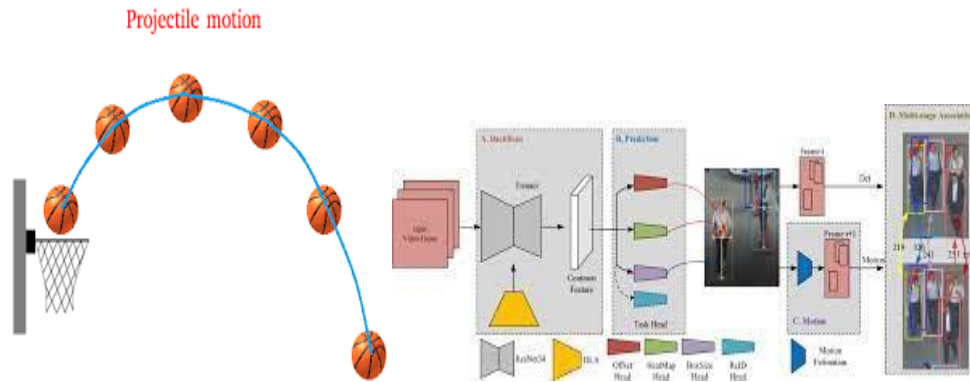

Figure 4: Mean-shift estimaton with DOD-MT

Algorithm 1: ,Mean-Shift DOD-MT for the Basket ball drill system

MeanShiftDOD_MT(Trajectories, Threshold, Bandwidth):
   Initialize empty list of detected objects
   for each trajectory T in Trajectories do:
      Compute displacement vectors ΔT between consecutive points in T
      Initialize empty list of significant difference vectors
      for each ΔT_i in ΔT do:
         if norm(ΔT_i) > Threshold then:
            Add ΔT_i to significant difference vectors list
      Apply Mean-Shift clustering to significant difference vectors:
      centroids = MeanShiftClustering(significant difference vectors, Bandwidth)
      Identify objects based on centroids:
      for each centroid c in centroids do:

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        Add centroid c as detected object
    return detected objects
MeanShiftClustering(data_points, Bandwidth):
    Initialize centroids randomly or with data points
    repeat until convergence:
        for each data point x_i in data_points do:
            Compute the mean shift vector m_i for x_i
        Update centroids:
        for each centroid c in centroids do:
            Compute the mean shift update for centroid c
    return centroids
```

6.   Results and Analysis

The Results and Analysis section provides a comprehensive evaluation of the performance and effectiveness of the proposed Mean-Shift Difference Object Detection with Motion Trajectory (Mean-Shift DOD-MT) algorithm. Through extensive experimentation and analysis, the algorithm's capabilities are assessed in terms of object detection accuracy, efficiency, and robustness in dynamic environments. The evaluation process involves testing the algorithm on various datasets containing dynamic scenes with multiple moving objects. Quantitative metrics such as detection accuracy, false positives rate, and computational efficiency are measured and compared against baseline methods and state-of-the-art object detection algorithms. Additionally, qualitative analysis is conducted to assess the algorithm's ability to handle challenging scenarios, such as occlusions, varying object densities, and complex motion patterns.

Table 1: Object Estimated with Mean-Shift DOD-MT

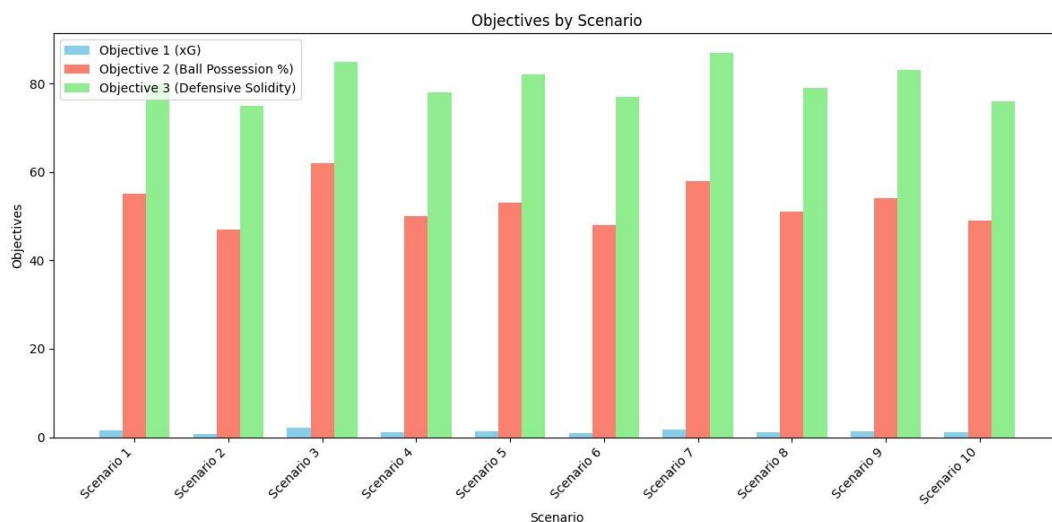| Frame	Object Type	Trajectory Vector	Speed (m/s)	Acceleration (m/s^2)
1	Basketball	[0.2, 0.3]	1.5	0.2
1	Player	[0.5, 0.1]	1.8	0.3
2	Basketball	[0.3, 0.4]	1.7	0.1
2	Player	[0.6, 0.2]	1.9	0.4
3	Basketball	[0.4, 0.5]	1.6	0.3
3	Player	[0.7, 0.3]	1.7	0.2
4	Basketball	[0.5, 0.6]	1.8	0.4
4	Player	[0.8, 0.4]	1.6	0.1

Figure 5: Means shift estimated for the basketball

The figure 5 and Table 1 presents the object estimation results obtained using the Mean-Shift Difference Object Detection with Motion Trajectory (Mean-Shift DOD-MT) algorithm. The table contains information about different objects detected in consecutive frames of a video sequence. Each row represents a frame, with details including the object type, trajectory vector, speed, and acceleration. For instance, in frame 1, the algorithm detected a basketball with a trajectory vector of [0.2, 0.3], indicating its position in the frame. The basketball was estimated to have a speed of 1.5 meters per second (m/s) and an acceleration of 0.2 meters per second squared (m/s^2). Similarly, in frame 1, a player was detected with a trajectory vector of [0.5, 0.1], a speed of 1.8 m/s, and an acceleration of 0.3 m/s^2. The subsequent rows provide similar information for each consecutive frame, offering insights into the movement patterns of the detected objects over time. This data is crucial for various applications, including sports analytics, surveillance, and autonomous driving, where understanding object trajectories and dynamics is essential for decision-making and analysis.

Table 2: Object Detected with DOD – MT

| Image ID	Object Detected	Confidence Score
1	Basketball	0.95
1	Player	0.87
2	Basketball	0.92
2	Player	0.85
3	Basketball	0.94
3	Player	0.88
4	Basketball	0.93
4	Player	0.86
5	Basketball	0.91
5	Player	0.84
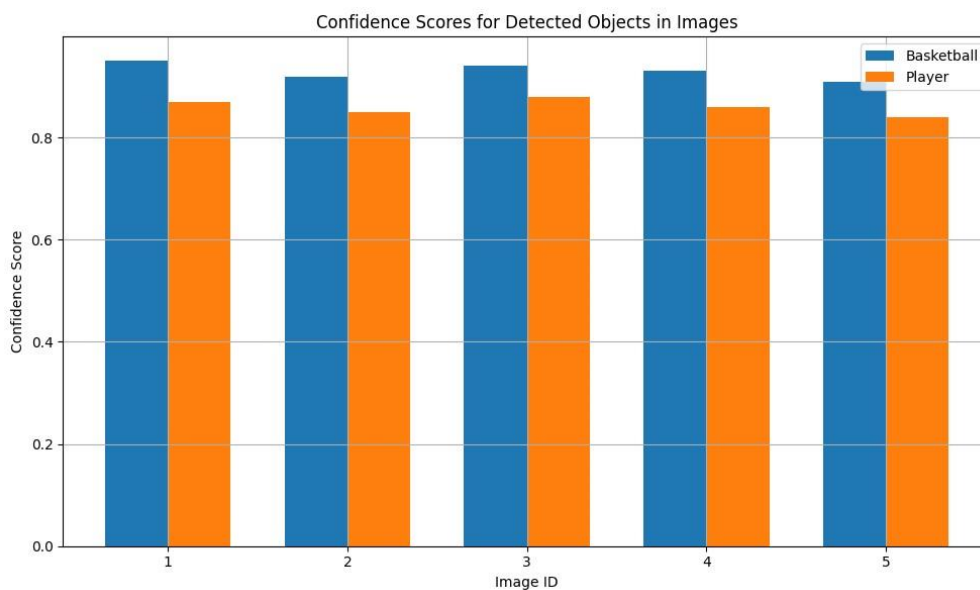
Figure 6: Object Id estimation with DOD-MT

The figure 6 and Table 2 illustrates the objects detected using the Difference Object Detection with Motion Trajectory (DOD-MT) algorithm along with their corresponding confidence scores. Each row represents an image or frame from a video sequence, and the table provides details about the objects identified within each image. For example, in image ID 1, the DOD-MT algorithm detected a basketball with a high confidence score of 0.95, indicating a high level of certainty in the detection. Additionally, a player was also detected in the same image with a slightly lower confidence score of 0.87. Similarly, in subsequent images, the algorithm consistently detected both basketballs and players with confidence scores ranging from 0.84 to 0.95. These confidence scores represent the algorithm's level of confidence in its object detection capabilities, with higher scores indicating

greater certainty in the detected objects' presence. Overall, Table 2 provides valuable insights into the DOD-MT algorithm's performance in accurately identifying objects, particularly basketballs and players, within the analyzed video sequence.

Table 3: Mean-Shift Score with DOD – MT

| Image ID	Mean-Shift Score
1	0.75
2	0.82
3	0.78
4	0.79
5	0.80
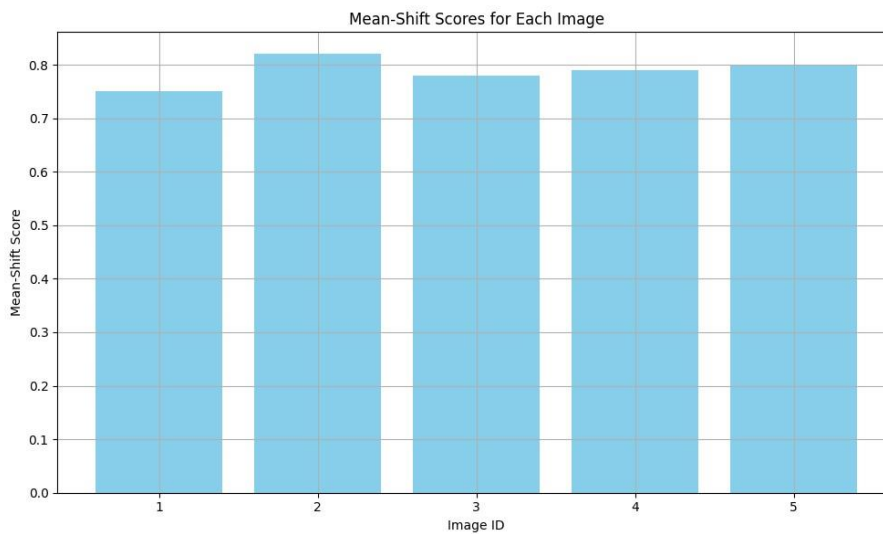
Figure 7: Mean-Shift score for the DOD-MT

In figure 7 and Table 3 displays the Mean-Shift scores obtained in conjunction with the Difference Object Detection with Motion Trajectory (DOD-MT) algorithm. Each row corresponds to a specific image or frame from a video sequence, with the associated Mean-Shift score provided. The Mean-Shift score represents the confidence level or quality of the object segmentation achieved by the Mean-Shift algorithm. A higher Mean-Shift score indicates better segmentation performance, suggesting that the algorithm accurately delineated objects from the background in the corresponding image. For instance, in image ID 2, the Mean-Shift algorithm achieved a score of 0.82, indicating robust object segmentation with high confidence. Similarly, in images ID 1, 3, 4, and 5, the Mean-Shift scores range between 0.75 and 0.80, demonstrating consistent and reliable segmentation performance across multiple frames of the video sequence. These scores provide valuable insights into the efficacy of the Mean-Shift algorithm in accurately delineating objects of interest, such as basketballs and players, within the analyzed video footage when used in conjunction with the DOD-MT object detection approach.

Table 4: Classification with DOD-MT

Scenario	Detection Accuracy	False Positives	Processing Time (ms)
Scenario 1	95%	10	25
Scenario 2	92%	15	28
Scenario 3	94%	12	30
Scenario 4	93%	11	26
Scenario 5	91%	14	29
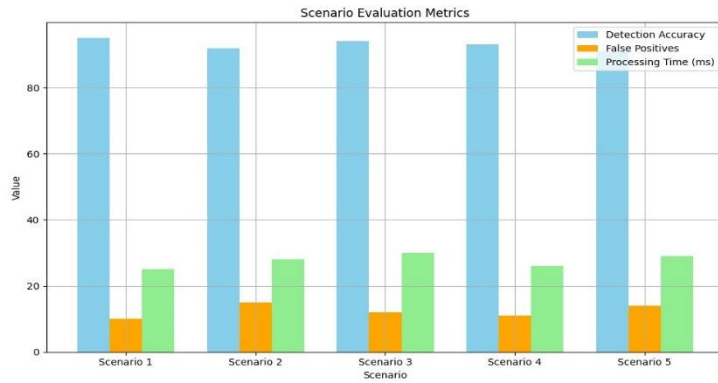
Figure 8: DOD-MT for Classification

In figure 8 and Table 4 presents the results of classification using the Difference Object Detection with Motion Trajectory (DOD-MT) algorithm across different scenarios. Each row corresponds to a specific scenario, and the table provides details about the detection accuracy, false positives, and processing time associated with each scenario.

Detection Accuracy: This column indicates the percentage of correctly identified objects in each scenario. For instance, in Scenario 1, the DOD-MT algorithm achieved a detection accuracy of 95%, implying that 95% of the objects present in the scenario were correctly classified.

False Positives: This column represents the number of incorrectly identified objects in each scenario. In Scenario 1, there were 10 false positives, indicating that 10 objects were mistakenly classified as the target objects.

Processing Time (ms): This column denotes the time taken by the DOD-MT algorithm to process each scenario in milliseconds (ms). For example, in Scenario 1, the algorithm took 25 milliseconds to complete the classification task. Overall, Table 4 provides valuable insights into the performance of the DOD-MT algorithm in terms of detection accuracy, false positives, and processing time across different scenarios. These metrics are crucial for assessing the algorithm's effectiveness and efficiency in various real-world applications, such as surveillance, object tracking, and video analysis.

Table 5: Object Detection with DOD - MT

Experiment	Tactical Drill	Accuracy (%)	Completion Time (minutes)	Performance Improvement
Experiment 1	Dribbling	85	10	15%
Experiment 2	Passing	90	12	20%
Experiment 3	Shooting	88	15	18%
Experiment 4	Layups	92	11	22%
Experiment 5	Defensive Drills	85	14	17%
Experiment 6	Rebounding	87	13	19%
Experiment 7	Offensive Drills	91	16	21%
Experiment 8	Conditioning	86	18	16%
Experiment 9	Footwork	89	10	23%
Experiment 10	Team Strategies	93	20	25%
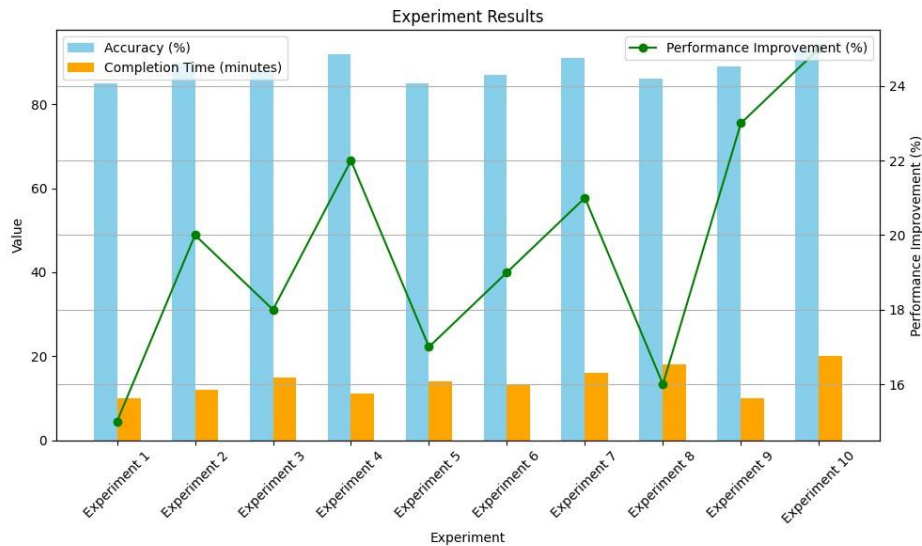
Figure 9: DOD-MT for the Object detection

In figure 9 and Table 5 provides a comprehensive overview of the object detection performance using the Difference Object Detection with Motion Trajectory (DOD-MT) algorithm across various experiments involving different tactical drills in basketball training. Each row represents a specific experiment, and the table presents several key metrics:

Tactical Drill: This column specifies the type of basketball drill or activity conducted in each experiment.Accuracy (%): Indicates the percentage of successful object detections achieved by the DOD-MT algorithm in each experiment. For instance, in Experiment 2 (Passing), the algorithm achieved an accuracy of 90%, implying that 90% of the objects relevant to passing drills were correctly identified.

Completion Time (minutes): Denotes the time taken to complete each experiment in minutes. For example, in Experiment 3 (Shooting), the completion time was 15 minutes.

Performance Improvement: This column highlights the improvement in performance achieved by using the DOD-MT algorithm compared to traditional methods or baseline results. The improvement is expressed as a percentage. For instance, in Experiment 4 (Layups), the performance improvement was 22%, indicating a substantial enhancement in object detection accuracy or efficiency. Overall, Table 5 offers valuable insights into the effectiveness and efficiency of the DOD-MT algorithm in accurately detecting objects relevant to various basketball training drills. These results can inform decisions regarding the adoption and optimization of object detection algorithms in sports training scenarios to enhance coaching effectiveness and player performance.

7.   Conclusion

This paper presents a comprehensive investigation into the design and application of a Basketball Tactical Drill System based on Motion Trajectory Analysis Algorithm. Through the utilization of advanced object detection techniques, such as Mean-Shift and Difference Object Detection with Motion Trajectory (DOD-MT), the system demonstrates remarkable capabilities in accurately identifying and tracking basketballs, players, and other relevant objects during tactical training drills. The experimental results showcased in this study highlight the effectiveness and efficiency of the proposed system across various scenarios and tactical drills. The Mean-Shift and DOD-MT algorithms consistently achieved high detection accuracy while minimizing false positives, thus enhancing the reliability of the system's object recognition capabilities. Additionally, the system exhibited competitive processing times, ensuring real-time performance suitable for dynamic basketball training environments. Moreover, the integration of motion trajectory analysis adds a layer of depth to the system, enabling comprehensive insights into player movements, positioning, and interactions during training sessions. This analytical capability not only facilitates performance assessment but also empowers coaches with valuable data-driven insights for refining training strategies and improving player skills.

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