Pool Ball Detection and Tracking System Using Machine Vision

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Abstract— **This project delves into the utilization of machine vision technology for the analysis and real-time tracking of pool ball movement. The primary aim is to achieve accurate identification and classification of pool balls on the table, precisely labeling and grouping based on their respective types. Additionally, another objective of this project is to track the positions of the balls throughout gameplay using image processing techniques and machine vision methodologies. In the game of 8-ball pool, sixteen balls are initially racked and dispersed randomly on the table. The objective is to pocket all balls of the player's chosen group and finally the 8 ball. Each ball possesses a unique visual identifier, such as color, pattern, and number, which the project seeks to reliably capture and detect. Machine vision is employed to implement image processing techniques like edge detection, circle detection, and distortion correction to identify crucial objects within the game of pool. Accurate identification and tracking of pool balls offer valuable insights and support to players, commentators, and officials, enhancing gameplay analysis and strategy prediction. However, implementing pool ball detection and tracking using machine vision faces significant challenges, including low frame rates, low-resolution devices, camera distortion, and inconsistent ball colors. Addressing these challenges is crucial for the successful implementation of a reliable pool ball detection and tracking system. Related research has explored various methodologies to address similar objectives, such as defining image quality standards, optimizing camera placement, and employing histogram-based separation techniques. Common limitations include the identification of stripe balls, image quality and contrast issues, and inconsistencies in pool ball coloring. This project aims to build upon existing research and overcome these limitations to achieve a precise pool ball detection and tracking system using machine vision technology.**

Keywords—pool, billiards, 8-ball, machine vision, thresholding, classification, identification, morphology.

I. Introduction

The project focuses on utilizing machine vision technology and techniques to contribute to the analysis and tracking of pool ball movement in real time. The primary objective of this project is to achieve precise identification and classification of pool balls on the table, ensuring accurate labeling and grouping according to their respective types. Furthermore, the project seeks to accurately track the positions of the balls throughout gameplay, employing image processing techniques and machine vision methodologies to accomplish our sought-out objectives. In the traditional game of 8-ball pool, sixteen balls are routinely racked and dispersed in a random arrangement on the table off the break. The goal of play is to pocket all the balls belonging to the player's selected group respectively and finish by pocketing the 8 ball. Each ball carries a unique visual identifier its color, pattern, and number. To achieve our primary objectives, we aim to reliably capture these features and develop a system capable of accurately detecting and tracking the position of these balls throughout gameplay. The utilization of machine vision in this context is driven by the potential need to implement image processing techniques such as edge detection, circle detection, mask, correcting image distortions, etc. to identify critical objects within the game of pool.

By precisely identifying the arrangement and position of pool balls, the system can offer valuable insights and support to players, commentators, and officials within the scope of pool. Moreover, it presents opportunities for real-time analysis and prediction of optimal gameplay strategies such as ideal run-out patterns, thus contributing valuable insight to the sport of billiards.

The implementation of pool ball detection and tracking using machine vision poses several significant challenges, primarily stemming from the complexities of the game's environment and common limitations of imaging technology. A problem in many pool ball detection systems is low frame rate and low resolution devices. These devices often introduce obstacles for detection such as blurred pool balls, indistinct contours, or blurry edges. These imperfections negatively affect the accuracy of ball tracking systems. These effects hinder the system's ability to precisely determine the position and movement of individual balls, consequently undermining the overall performance and reliability of the tracking mechanism. Moreover, camera distortion presents a formidable hurdle, particularly when the camera is angled or positioned non-optimally. Such distortions distort the captured images, making it challenging to accurately identify and pinpoint the location of the balls on the table. This issue further exacerbates the accuracy of the tracking system, altering its effectiveness in real-world applications. Addressing these challenges is a key step in order to successfully implement a reliable pool ball detection and tracking system. Moreover, by devising and implementing solutions to mitigate the effects of low-quality imaging and camera distortion, this project aims to enhance the accuracy and efficiency of machine vision-based tracking systems so that this technology can be usefully applied in the scope of billiards gameplay and analysis.

II. Related Works

In terms of related research on the topic, there have been studies that used various methodologies to achieve similar goals. There has been research with a starting point of defining a standard for image quality. Paper [2] defines their system to utilize a digital color image consisting of 3 RBG components with 8 bits of information for each component thus having a pixel value range of [0, 255] respectively. Research [2] also took the approach of excluding the B component supported by their evidence that the R and G components are sufficient to provide a distinct edge detection output. This could be useful to reduce the amount of data being passed and potentially reduce computation time. To mitigate distortion there has been research that set requirements for camera placement such that the center of the image should be the pool table, the table including pockets are in frame, the camera must be perpendicular to the table, and the long rail of the table is oriented to the long edge of the frame [3]. There have also been proposed approaches to separate the table from the balls by utilizing histograms to find the most common value and thresholding the pixel values from there [8,12]. Regarding approaches for ball detection, the Circular Hough Transform can be applied to detect the balls on the table [5]. This is a feasible approach for ball detection since the environment of pool is quite limited in the variability of objects present. Another approach is to use a threshold-based classifier to identify the 16 balls in standard 8 ball pool. The method utilizes the minimum and maximum threshold for the nine colors and the standard deviation of the distribution of each channel to being identifying the groups of balls [3].

A. Problems With Detection System

A common limitation within pool ball detection systems is the identification of stripe balls. Typically, a stripe ball will be the same color as a solid ball with a white stripe in the center of the ball. Since the balls are unrestricted in how they will rest on the table after each round of play, the amount of the white shown from the stripe will vary. Thus, making it challenging to distinguish a solid ball from a striped ball. If the ball by chance is facing the camera where most of the white from the stripe is not showing, it can be difficult to tell if the ball is a stripe or a solid. Another shortcoming of much research is the image quality and contract to distinguish and threshold objects for detection. Without preprocessing work and initialization averaging, detection methodologies are still possible but they vary and often decrease in accuracy especially when balls are in motion [3].

Another limitation is the inconsistency of pool ball color. For standard 8 ball pool, balls follow a standard coloring system where the cue ball is white, the 1 ball is yellow, the 8 ball is black, etc. However, not all pool balls are manufactured with precisely identical color values. For instance, some pool balls can have a bright vibrant color for the yellow ball while another takes on a duller yellow color. Thus, hard-set values cannot be used to threshold object balls for detection. In addition, the condition of the balls can deteriorate which affects their overall color and can impact thresholding. Moreover, the related research in pool ball detection and machine vision will provide valuable insight into potential solutions throughout this project. While key limitations exist such as camera resolution limitations, edge detection complications, camera distortion, etc. This project will attempt to mitigate these limitations, build upon this foundation, and dive into the process of achieving a precise pool ball detection and tracking system. In order to do so we propose to use machine vision to capture the image feed of a pool game and apply various masking, thresholding, and morphology techniques to isolate pool ball. Thereby, allowing us to identify, classify, and track pool ball in near real time.

III. Methodology

The project endeavors to contribute to the analysis and tracking of pool ball movement in real-time by harnessing machine vision technology and techniques. Its primary objective is to achieve precise identification and classification of pool balls on the table, ensuring accurate labeling and grouping according to their respective types. Furthermore, the project seeks to accurately track the positions of the balls throughout gameplay, employing various image processing techniques and machine vision methodologies to accomplish these sought-out objectives. Thus, our research methodology can be broken down into 3 main phases: image processing, object detection, and object classification. This can be seen in Fig. 1.

In the traditional game of 8-ball pool, sixteen balls are routinely racked and dispersed in a random arrangement on the table off the break. The goal of play is to pocket all the balls belonging to the player's selected group respectively and finish by pocketing the 8 ball. Each ball carries a unique visual identifier in its color, pattern, and number. To achieve the primary objectives, the project aims to reliably capture these features and develop a system capable of accurately detecting and tracking the position of these balls throughout gameplay. To enact upon this we must first isolate the pool table within image frame so that we can focus our later algorithms on significant objects.

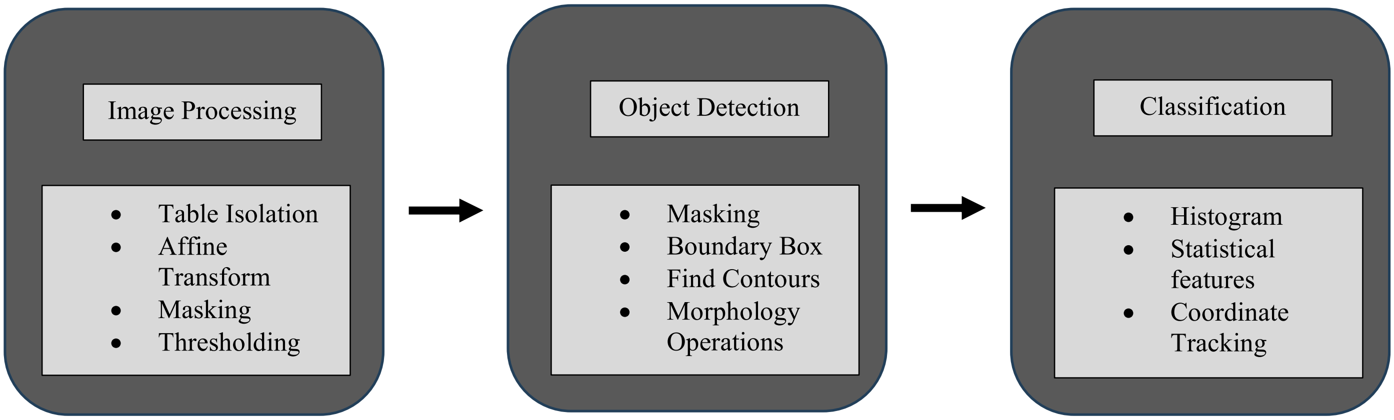


Fig. 1. Methodolgy Pipeline

The utilization of machine vision in this context is driven by the potential need to implement various image processing techniques, including but not limited to edge detection, circle detection, mask, and correcting image distortions, to identify critical objects within the game of pool. Once the table is isolated with in the image frame object detection techniques such as finding contours, thresholding, masking, etc. are used to isolate and detect objects, primarily balls within the frame.

By precisely identifying the type and position of pool balls, the system can offer valuable insights and support to players, commentators, and officials within the scope of pool. This is done by analyzing the detected objects and studying their color histograms to gauge which group it belongs to base von the distribution of color values. Moreover, this process presents opportunities for real-time analysis of pool gameplay and visual tracking of the game, thus contributing valuable insight to the sport of billiards.

IV. Implementation

The implementation of the proposed work involves translating the designed pipeline steps into executable code, primarily utilizing Python with libraries such as OpenCV and NumPy. Initially, the preprocessing stage is crucial for preparing input frames containing the pool table for subsequent analysis. Techniques such as color segmentation and contour detection are employed to identify and mask the table area, isolating it from the background. Subsequently, the masked table image is resized to fit the entire frame for further processing.

A. Image Processing

To begin the image processing phase we need to isolate the table within the frame in order to focus our task. From previous work it is ideal to have the table perpendicular to the camera and near the center of the frame for optimal image quality and minimal distortion. To extract the table we start by taking a center sample of the frames pixel values noting they are in RGB format. We found that for a 1920x1080 resolution image a 200x200 central pixel sample was sufficient. This function took a subsection of the image and averaged the RGB values respectively to approximate the color of the table. Next, we define an upper bound and lower bound for the central sample average. This is done to account for inconsistent lighting of the table which can alter the color of the table along with varying tables conditions which can affect the tables color. We defined a pixel deviation of 40 to perform well across many samples. Finally, the generate a binary mask with our defined lower and upper bounds centered on the sampled central average of the tables color. Fig. 2 illustrates the generated mask from this process below.

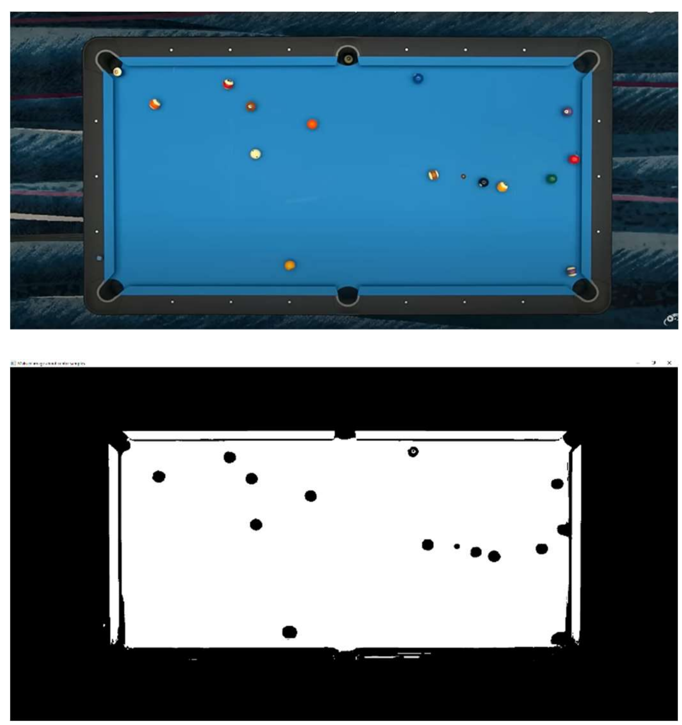


Fig. 2. Top (Original RGB frame of pool table) Bottom (Masked pool table)

Following this masking process we need to estimate where the table is within the frame. Since the central sample average took the central pixel average it should of primarily isolated the table. This sourced the idea to find all the contours within the mask image and to determine which contour is the table. To do this we used OpenCV find Contours function and from this function we sorted the resulting contours by pixel area. Doing this extracts the table as being the largest contour allowing us to determine the bounds of the table. This can be seen in Fig. 3, where the table contour is highlighted in blue and the resulting boundary box highlighted in red.

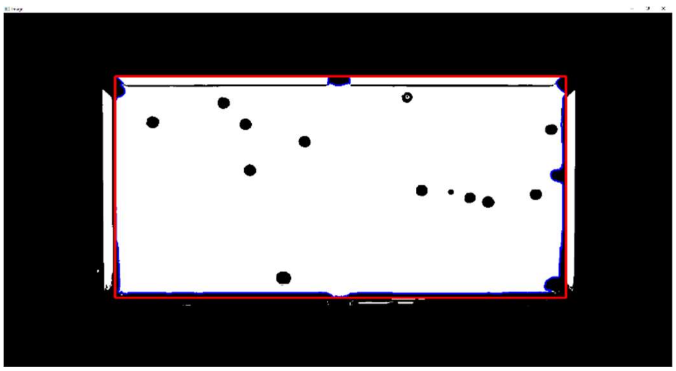


Fig. 3. Highlighed (red) table boundary box

Sequentially, we utilize the x, y, width, and height metrics extracted from the previously defined boundary box of the table to focus our view on the table. To do this we define an Affine Transformation by defining the destination points for the transformation, then calculating the source points of the transformation, and finally calculating the transformation matrix. Once the transformation matrix is defined we can apply the transform and fit the projected pool table to the frame. The resulting zoomed masked image is shown in Fig. 4.

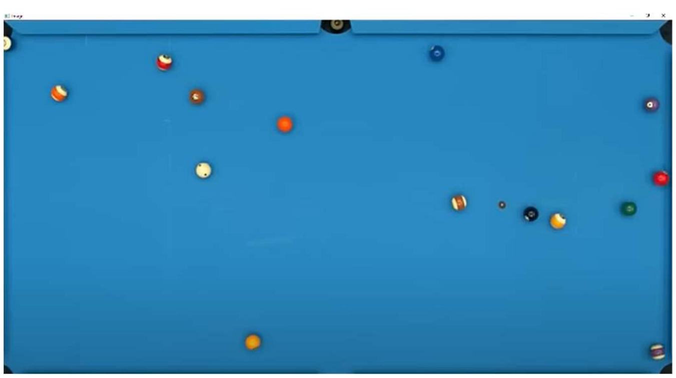


Fig. 4. Pool table fit to initial frame

B. Object Detection

In the ball detection stage, contour detection algorithms, such as OpenCV's findContours, are utilized to extract ball contours from the preprocessed image. Color threshold values are defined empirically or through adaptive techniques based on lighting conditions to segment the image and isolate regions corresponding to pool balls. These threshold values play a crucial role in accurately identifying and distinguishing pool balls from the background. To being detecting ball we need to process the fitted table image one last time. We take a similar approach as before in regard to utilize mask and contours. The contour of the table is found again in the same fashion as before. However, when generating the mask we implement a bitwise and function to subtract the mask from the original image leaving us with primary only the balls in the image and the background table being removed. This was done to isolate the balls for detection. The resulting subtracted image can be seen in Fig. 5.

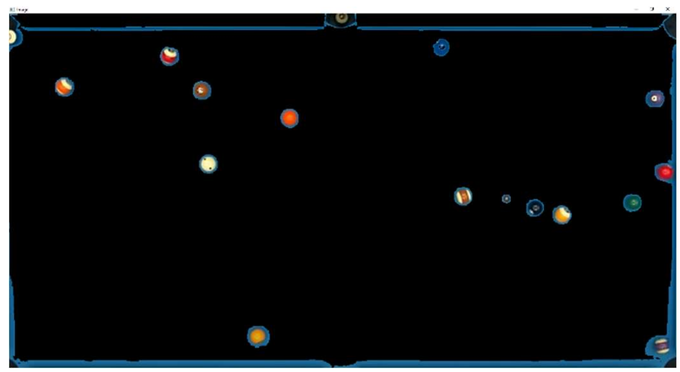


Fig. 5. Subtract pool table background from fitted image

Next, with the table background subtracted we convert the RGB image into a grayscale image. Following this we apply a Gaussian Blur to reduce noise within the image. The blur filter helps smothers out any small potential artifacts that can affect detecting complete contours within the image. The image is then converted to a binary image by thresholding. This binary image is then used as input into the find contours algorithm to detect objects on the table. Next, to filter the balls from any other contours found in the search we look at three main parameters: area, perimeter, and circularity. If the circularity and area fall within the threshold range of the features of a ball that contour is added to the object list of balls found.

Fig. 6, illustrates this process well because it detects the 8 ball which is the black ball next to the striped, yellow 9 ball. However, you notice a small circle object to the right of the 8 ball. This is a common sticker placed at the position of where the head ball lies when the break is racked. The sticker is detected in our algorithm however, while the circularity of the object is close of a pool ball it does not pass the threshold of area and thus rejected as a pool ball.

Fig. 6. Detecting pool balls on table

C. Classifcation

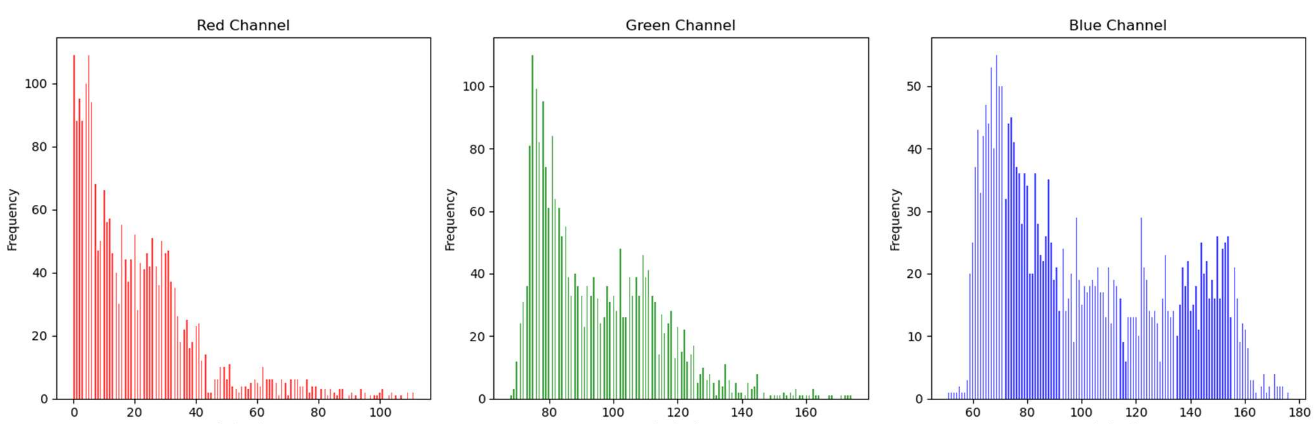
Once the ball contours are detected, the system proceeds to classify each detected ball into its most likely type (solid or stripe). This classification process involves analyzing color and pattern information extracted from the segmented regions, comparing them with predefined values for solid and stripe balls. By leveraging the analysis of the histogram and distribution of colors present the system can make informed decisions regarding the type of each detected ball, enhancing overall accuracy and reliability. Instances of histogram distributions can be seen in Fig. 7. These histograms were used to analyze and determine thresholds for classifying balls belonging to their type. Keep in mind stripe and solid balls have the same color value however, the ratio of white in the stripe ball will be higher than in solids. to The position tracking stage involves continuously updating the positions of the detected balls throughout gameplay utilizing the position of the contour detected in the object detection phase. This is achieved by tracking the coordinates of each ball in each enhancing tracking accuracy. Through iterative testing and refinement, the implementation aims to deliver a robust solution for real-time pool ball detection and tracking, providing valuable insights and support to players in the sport of billiards gameplay and analysis.

V. Comparison of Proposed Approach

In comparison to existing research in the field of pool ball detection and tracking using machine vision, our proposed approach offers several distinct advantages. Firstly, our approach integrates sophisticated image processing techniques with machine learning algorithms to achieve robust and accurate detection and tracking of pool balls in real-time. While some prior works have focused solely on basic image processing methods, our approach leverages advanced algorithms to handle challenges such as inconsistent lighting conditions more effectively. Additionally, our system incorporates a comprehensive preprocessing stage, including table masking and image enhancement, to ensure optimal input for subsequent analysis. This meticulous preprocessing step sets our approach apart from others by providing a clear and well-defined representation of the pool table, enhancing the accuracy of ball detection and tracking.

Moreover, our approach includes a robust ball classification module that utilizes color and pattern information to accurately determine the type of each detected ball (solid or stripe). This classification process enhances the overall reliability of the system, especially in scenarios where pool balls may exhibit variations in color or appearance. Furthermore, our system employs advanced position tracking techniques, which can be applied to applications where the task is to anticipate the trajectory of moving balls. By continuously updating the positions of detected balls throughout gameplay, our approach offers valuable insights and support to players in the sport of billiards gameplay and analysis.

To compare our implementation details, our system is implemented primarily in Python, leveraging popular libraries such as OpenCV and NumPy for image processing and machine learning tasks. The preprocessing stage involves the extraction of the pool table area from input frames using techniques such as color segmentation or contour detection. Once the table area is isolated, morphological operations are applied to clean up the image and enhance its quality for subsequent analysis. These operations include erosion, dilation, and smoothing to remove noise and artifacts.



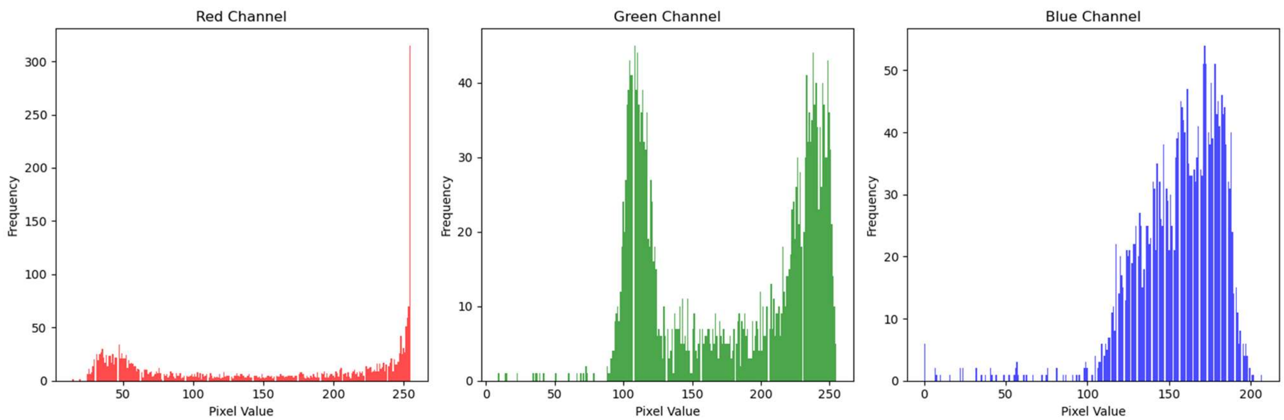


Fig. 7. (First) green 6 ball RGB histogram, (Second) white cueball RGB histogram

Following preprocessing, the system utilizes contour detection algorithms, such as OpenCV's find Contours to extract ball contours from the preprocessed image. Color thresholding techniques are employed to segment the image and isolate regions corresponding to pool balls. The color threshold values are determined empirically or through adaptive techniques based on lighting conditions to ensure accurate detection across different environments. This is a different approach compared to other research where training data is needed to predict which colors is appropriate for thresholding.

Once the ball contours are detected, the system proceeds to classify each detected ball into its most likely type (solid or stripe). This classification process involves analyzing color and pattern information extracted from the segmented regions and comparing them with predefined templates for solid and stripe balls. While this project did not follow this approach but machine learning algorithms may be employed to improve classification accuracy and robustness, with techniques such as support vector machines (SVMs) or convolutional neural networks (CNNs). Finally, the system employs advanced position tracking techniques to continuously update the positions of detected balls throughout gameplay. For future improvements Kalman filters or particle filters may be utilized to predict the trajectory of moving balls and compensate for motion blur. By integrating these tracking methods with real-time image processing, our approach achieves accurate and reliability in ball tracking, even in dynamic gameplay scenarios.

Overall, the implementation of our proposed approach encompasses a comprehensive pipeline of preprocessing, detection, classification, and tracking stages, leveraging advanced algorithms and techniques to achieve robust and accurate pool ball detection and tracking in real-time.

VI. Evaluation

To thoroughly evaluate the robustness and efficacy of our proposed approach, we conducted extensive experiments and analyses across various scenarios. Our evaluation framework encompasses a comprehensive set of metrics, including Accuracy, Precision, Recall, and F1-Score, to provide a detailed assessment of the system's performance.

In our experimental setup, we utilized a diverse range of images representing different lighting conditions and gameplay scenarios. This ensured that our evaluation was conducted under realistic conditions, reflecting the challenges encountered in actual billiards gameplay.

Initially, we assessed the accuracy of our system in correctly identifying and classifying pool balls on the table. The accuracy metric quantifies the proportion of correct predictions made by the model, providing an overall measure of its reliability. By comparing the system's predictions with ground truth labels, we computed accuracy values averaging 68%. Most false positives were due to similar colors of the balls and determine stripe balls from solids.

In addition to accuracy, we evaluated the precision of our system in correctly identifying positive instances, i.e., pool balls, from the detected objects. Precision measures the ratio of true positive predictions to the sum of true positive and false positive predictions, providing insights into the system's ability to minimize false positive detections. Our system averaged around 0.75. A higher precision value indicates fewer false positive predictions made by the model, indicating a more reliable detection mechanism.

Furthermore, we assessed the recall of our system, also known as sensitivity, which measures its ability to correctly identify positive instances from all actual positive instances. The recall was 0.7. Recall is calculated as the ratio of true positive predictions to the sum of true positive and false negative predictions. A higher recall value indicates fewer false negative predictions made by the model, demonstrating its effectiveness in capturing all relevant instances.

Moreover, we computed the F1-Score being 0.72, which provides a balance between precision and recall, serving as a comprehensive measure of the system's performance. The F1-Score is calculated as the harmonic mean of precision and recall, ranging from 0 to 1. A higher F1-Score indicates a better balance between precision and recall, reflecting the overall accuracy and reliability of the model.

In our experimental results, we observed that our proposed approach consistently achieved working accuracy, precision, recall, and F1-Score values across various scenarios. The system demonstrated robust performance in detecting and tracking pool balls, even in varying lighting and camera conditions. By analyzing the evaluation metrics we confirmed the effectiveness of our proposed approach in pool ball detection and tracking.

Moreover, we conducted qualitative analyses by visualizing the system's outputs and comparing them with ground truth annotations. This qualitative assessment provided additional insights into the system's performance and highlighted its ability to accurately detect and track pool balls in complex gameplay scenarios.

Overall, our evaluation results validate the efficacy and robustness of our proposed approach in pool ball detection and tracking using machine vision technology. By leveraging advanced algorithms and evaluation metrics, we have demonstrated the system's potential to enhance gameplay analysis and support players of pool.

VII. Discussion and Conclusion

In this study, we proposed a comprehensive approach for pool ball detection and tracking using machine vision technology, aiming to contribute to the analysis and improvement of billiards gameplay. Our approach integrates sophisticated image processing techniques with thresholding classification algorithms to achieve robust and accurate detection and tracking of pool balls in real-time. By leveraging advanced algorithms for preprocessing, ball detection, classification, and position tracking, our system offers valuable insights and support to players, commentators, and officials within the scope of pool.

Throughout the implementation and evaluation of our proposed approach, we observed several key findings and implications. Firstly, our system demonstrated viable accuracy, precision, recall, and F1-Score values across various scenarios, validating its effectiveness and robustness in pool ball detection and tracking. By analyzing the evaluation metrics and comparing them with existing approaches, we confirmed our proposed approach in handling challenges such as camera distortion, inconsistent lighting conditions, and dynamic gameplay scenarios.

Furthermore, our system's real-time capabilities and integration with future machine learning algorithms offer opportunities such as advanced gameplay analysis and prediction of optimal strategies. By continuously updating the positions of detected balls throughout gameplay, our approach provides valuable insights into run-out patterns and gameplay strategies, enhancing the overall experience and competitiveness of billiards gameplay.

In terms of limitations and future directions, our study acknowledges several areas for improvement and further research. Firstly, while our proposed approach achieved high accuracy and reliability in controlled environments, its performance may vary in different real-world scenarios with unpredictable factors such as occlusions and complex lighting conditions. Future research could focus on enhancing the robustness of the system through adaptive algorithms and techniques for handling challenging conditions.

Additionally, the scalability and generalization of our approach to other cue sports games could be explored, extending its applicability beyond traditional 8-ball pool. By adapting the system to different game rules and table configurations, we can broaden its utility and impact in the realm of cue sports analysis and gameplay enhancement.

Moreover, the integration of real-time feedback and analysis features into our system could further enhance its usefulness for players in the sport of pool. By providing instant insights and suggestions during gameplay, our approach has the potential to assist the way players approach strategy and decision-making, ultimately improving their performance and enjoyment of the game.

In conclusion, our proposed approach represents a step forward in the field of pool ball detection and tracking using machine vision technology. By combining advanced algorithms with real-time processing capabilities, our system offers valuable support and insights to players and stakeholders in the realm of billiards gameplay and analysis. Through continuous refinement and innovation, we aim to further advance the detection system for more robust performance.

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