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AUTOMATED DETECTION AND ANALYSIS OF PROJECTILE IMPACTS USING COMPUTER VISION

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ABSTRACT

This paper presents a software system for the automated real-time detection, stabilization, and analysis of projectile impacts in video sequences. The system utilizes a model to identify the region of interest automatically. Impact events are identified through a multi-method approach that combines the inter-frame transformation magnitudes, background subtraction, and contour analysis within a defined mask. The system outputs annotated frames marking the precise impact location and calculates its coordinates relative to the center of the target.

Keywords: Impact Detection, Computer Vision, Optical Flow, Video Stabilization, Background Subtraction

Introduction

Accurately detecting and localizing impact points in video sequences is an important task in various domains, including sports analytics, defense applications. Manually reviewing footage to identify and localize these events is time-consuming and prone to human error.

Traditional motion detection algorithms, while simple and efficient, are often prone to false positives caused by minor camera movements, lighting changes, or irrelevant background motion. More advanced systems use high-speed cameras or additional sensors to achieve higher precision, but such setups are costly and less accessible. With the growing availability of high-resolution video and advances in computer vision, it is now possible to achieve similar accuracy using standard cameras combined with intelligent image processing techniques.

Existing approaches often rely on background subtraction [1, 2], but these can be sensitive to dynamic backgrounds. More recent methods incorporate deep learning for object detection [3, 4], but real- time performance and accurate localization remain challenges.

While many existing approaches focus on detecting impacts on a fixed target (e.g., a gong), real- world scenarios frequently involve shots that miss the target and hit the surrounding ground. These ground impacts carry valuable information –

for example, for adjusting aim, evaluating projectile spread, or tracking shot trajectories.

Related Work

The detection and localization of impact events in video intersect several key areas of computer vision, including motion detection, video stabilization, background modeling, and object detection. Traditional methods, such as frame differencing and background subtraction (e.g., Gaussian Mixture Models [1] or running averages [2]), are computationally efficient but often fail in real-world conditions due to camera motion, dynamic backgrounds, and illumination changes.

Video stabilization has been widely studied to mitigate the effects of camera shake. Classical feature-based methods, including those based on the Kanade-Lucas-Tomasi (KLT) optical flow [5] or SIFT/SURF feature matching [6], estimate inter-frame transformations to compensate for unwanted camera shake. More recent stabilization approaches leverage homography estimation and motion smoothing [7], enabling more robust separation between scene motion and camera-induced motion. However, these methods are typically applied offline and are not optimized for real-time impact detection tasks.

For object localization, deep learning-based methods such as Faster R-CNN [3], YOLO [4], and more recently, Segment Anything Model (SAM) [8], have achieved high accuracy and generalization, but are not well suited for transient, small-scale events such as projectile impacts. Recent variants such as Fast

Segment Anything Model (FastSAM) [9] offer real-time segmentation performance, making them suitable for target identification in streaming video.

Some approaches focus exclusively on detecting impacts on a fixed target, such as gongs or metallic plates, using vibration analysis or frame differencing. However, these methods are limited to hits within a predefined area and fail to detect ground impacts, which can be critical for applications such as ballistic calibration or trajectory reconstruction.

In summary, existing techniques either rely on motion cues that are sensitive to environmental factors or on object detectors not optimized for short, transient events. The proposed system addresses this gap by combining real-time target segmentation, feature-based stabilization, and a multi-method detection strategy to robustly detect and localize both target and ground impacts.

Proposed Method

The proposed system is designed as a modular pipeline that integrates several computer vision techniques to achieve robust, real-time impact detection. The overall architecture, depicted in Figure 1, consists of five main stages: (1) video input and preprocessing, (2) target identification and initialization,

(3) frame stabilization and motion compensation, (4) multi-method impact detection and analysis, and (5) data fusion and output. The following subsections provide a detailed exposition of each stage.

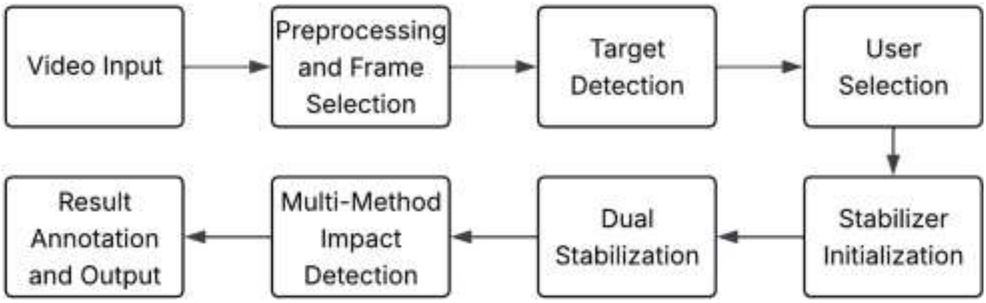


Figure 1. System Architecture Diagram.

1. Video Input and Processing

The process begins by capturing the video stream from a file or a live camera feed. Each frame is resized to a fixed resolution (e.g., 1280×720) to standardize processing and reduce computational load. A preprocessing step removes black areas caused by the phone being attached to binoculars, ensuring that only the relevant visual region is analyzed and reducing unnecessary computation.

2. Target Identification and Initialization

Accurate and stable target identification is critical for reliable impact localization. This is achieved by using the FastSAM segmentation model, which provides high accuracy and real-time performance.

From the segmented output, candidate regions are extracted based on confidence scores and presented to the user for manual confirmation. This user-in-the-loop initialization ensures precise target selection (e.g., the gong), which is used to initialize the stabilization module.

3. Frame Stabilization and Motion Compensation

To separate true impact motion from camera shake, the system applies feature-based video stabilization. After the target is selected, keypoints are extracted from the reference frame (frame after target selecting) and tracked across subsequent frames using the Kanade–Lucas–Tomasi (KLT) optical flow algorithm. For each keypoint $p_j = (x_j, y_j)^T$ in the reference frame, the corresponding $p'_j = (x'_j, y'_j)^T$ in the current frame is found. The matched feature pairs are used to estimate a partial affine transformation matrix:

$$p'_j \approx A_t \begin{bmatrix} p_j \\ 1 \end{bmatrix}, A_t = \begin{bmatrix} a_{11} & a_{12} & t_x \\ a_{21} & a_{22} & t_y \end{bmatrix}.$$

Each frame is warped using the inverse of this transformation to produce a stabilized video stream in which the target remains stationary. The magnitude of motion is computed as:

$$\Delta t = \sqrt{t_x^2 + t_y^2},$$

and stored for subsequent impact detection.

4. Multi-Method Impact Detection and Analysis

Impact detection combines two complementary methods for reliability.

Method 1: Transformation Magnitude-Based Detection. This method acts as a high-confidence trigger. A projectile impact typically induces a sudden, sharp impulse to the target, causing a momentary, large displacement. This manifests as a significant peak in the magnitude of the stabilization transformation. When this magnitude exceeds a dynamically adaptive threshold, it is interpreted as a primary indicator of a hit event, initiating the relevant frames saving process.

Method 2: Contour Analysis within a Region of Interest (ROI). This method provides precise impact localization. A dynamic background model B_t of the target is maintained using a running average:

$$B_t = (1 - \alpha) \cdot B_{t-1} + \alpha \cdot I_t^{ROI},$$

where I_t is the original frame, $B_0 = I_0^{ROI}$, and $0 \le \alpha \le 1$. This background model blends information from each new frame with the existing background. This allows the model to adapt to slow, natural changes (such as lighting variations) while ignoring short, sudden disturbances. The absolute difference between the current target ROI and this background model is computed and thresholded to create a binary mask of changes.

Contours extracted from this mask are filtered to remove edge noise and combined using a custom merging algorithm.

The algorithm works by computing the distance between contour centroids. For two contours with centroids at positions $c_i = (x_i, y_i)$ and $c_j = (x_j, y_j)$, the distance is calculated as:

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}.$$

Contours with centroids closer than a distance threshold, $d(i,j)\tau_{dist}$, where τ_{dist} is a predefined distance threshold, are joined if their merged convex hull area is within an acceptable range.

Remaining contours are evaluated for circularity, defined as:

$$C = \frac{4\pi A_c}{p_c^2},$$

where A_c and P_c are the contour's area and perimeter. This metric ranges from 0 (complex shape) to 1 (perfect circle). Contours with $C > \tau_{cric}$ are classified as valid impact points, where τ_{cric} is a predefined circularity threshold. This ensures only circular patterns characteristic of projectile impacts are selected.

5. Data Fusion and Output

When a hit is confirmed by either method, the system synthesizes the data. The impact coordinates are transformed back to the original frame's coordinate system using the inverse of the stabilization transformation matrix. As we have 2 × 3 affine transformation matrix A_t is first converted to a 3 × 3 homogeneous matrix:

$$A_{hom} = \begin{bmatrix} & A & \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & t_x \\ a_{21} & a_{22} & t_y \\ 0 & 0 & 1 \end{bmatrix}.$$

The inverse transformation A_{hom}^{-1} is computed, and the impact point $p_{stab} = (x, y, 1)^1$ in homogeneous coordinates is transformed as:

$$p_{original} = A_{hom}^{-1} \cdot p_{stab}\ .$$

The system then calculates the normalized offset relative to the target's center, providing metrics such as "X: 0.125 LEFT", which indicates the hit was located 12.5% of the target's width to the left of center. The final annotated frame displays the target boundary, detected impact point, and offset information, as shown in Figure 2.

Results

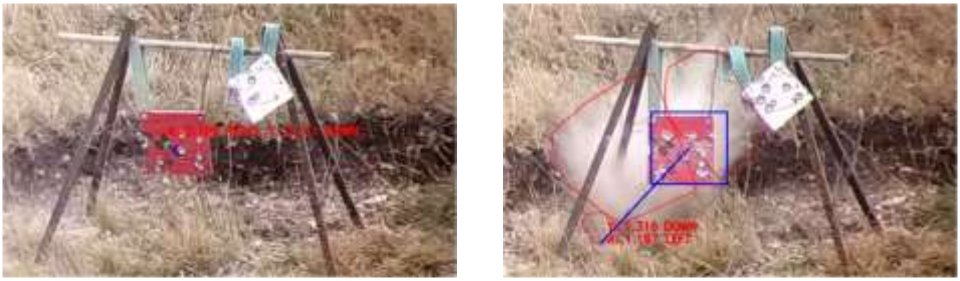
To evaluate the performance of the proposed system, we compiled a dataset consisting of 71 videos, each approximately two minutes long. The dataset includes a range of scenarios: videos with no impacts, only gong hits, only off-target (ground) impacts, and those containing both. This diversity allows for a comprehensive evaluation of both gong and non-gong impact detection.

After processing the entire dataset, the system produced a total of 227 annotated detections, each of which was manually reviewed and classified. The distribution of detections is summarized in Table 1.

Table 1. Results of system testing.

Category	***Description***	***Count***
Correct off-target detections	Hits not on the gong but correctly localized	159
Correct gong detections	Hits on the gong, correctly localized	26
Gong detections with localization error	Hits on the gong, detected but with incorrect impact location	7
Off-target detections with localization error	Hits not on the gong, detected but with incorrect impact location	10
Unrelated / ambiguous detections	False detections caused by camera shake or duplicate detections from multiple methods	25

In total, 185 out of 227 detections (81.5%) were correctly localized, demonstrating the system's ability to accurately identify both gong and off-target impacts. The remaining 11% of ambiguous detections were mainly caused by strong camera motion or simultaneous activation of multiple detection methods. These cases suggest directions for future improvement, such as implementing temporal filtering and decision fusion strategies to further enhance system stability and precision.



(a) (b)

Figure 2. Representative examples of successful impact detection: (a) On-target hit accurately detected and measured on the gong surface; (b) Off-target hit correctly localized in the background.

Conclusion

In conclusion, the implemented system demonstrates a robust and effective approach to automated impact detection. This system has practical applications in automated scoring systems, scientific experiments, and security monitoring.

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АВТОМАТИЗИРОВАННОЕ ОБНАРУЖЕНИЕ И АНАЛИЗ ВОЗДЕЙСТВИЙ СНАРЯДОВ С ИСПОЛЬЗОВАНИЕМ КОМПЬЮТЕРНОГО ЗРЕНИЯ

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АННОТАЦИЯ

В данной работе представлена программная система для автоматического обнаружения, стабилизации и анализа попаданий снарядов в видеопоследовательностях в режиме реального времени. Система автоматически определяет область интереса с помощью модели сегментации. События попаданий выявляются с помощью многоуровневого подхода, который сочетает анализ межкадровых преобразований, вычитание фона и контурный анализ в заданной маске. На выходе система формирует аннотированные кадры с точным указанием места попадания и вычисляет его координаты относительно центра цели.

Ключевые слова: обнаружение ударов, компьютерное зрение, оптический поток, стабилизация видео, вычитание фона.