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# SHADOW REMOVAL OF FOREGROUND DETECTION IN VIDEO SURVEILLANCE SYSTEM

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## ABSTRACT

Shadows are natural phenomena, which occur when the light is blocked. Although shadows provide important visual cues for object shape perception, illumination position, objects occlusion, etc., shadow-free images can help to improve the performance of the tasks such as object recognition, object tracking and information enhancement. For example, for high spatial resolution remote sense image, shadow removal is very critical for target identification and information recovering. Shadow removal and editing can also improve the visual realism and physical realism in image processing. Shadow removal is now an popular research direction in computer vision and image processing communities.The first problem to be addressed is shadow detection. For image with complex shadows, exactly shadow detecting is a difficult problem. For example, sometimes it is even difficult for human to differentiate little dark objects from the scattered shadow points. The second one is When the illumination conditions, object materials, and scene shapes are complex, the shadows in the image are usually non uniform, which makes it difficult to obtain consistent shadow removal results. Finally, as the illumination usually changes dramatically in the boundary regions, effectively recovering the illumination on the shadow boundaries is also a challenging task. In this project, we present a novel shadow removal approach using an illumination recovering optimization method. We first detect the shadows in the input image, and compute the shadow alpha for the shadows. Then we adaptively decompose the input image into overlapped patches according to the shadow distribution. Denser patches are put on the shadow boundaries and the regions with dramatically changed illumination. Finally, by building the correspondence between the shadow patch and the lit patch based on illumination independent texture similarity, we develop an optimized illumination recovering operator which can effectively remove the shadows and recover the texture detail under the shadow patches.In stage 2 improve the PSNR value with shadow image and shadow free image

## I.INTRODUCTION

In the digital age, video surveillance systems have become ubiquitous tools for enhancing security, managing traffic, monitoring public spaces, and supporting intelligent decision-making in smart cities. With the growing demand for automated, real-time surveillance systems capable of reducing human monitoring efforts, the importance of robust and efficient computer

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vision techniques has grown exponentially. At the core of many computer vision-based surveillance applications lies **foreground detection**—a critical pre-processing step responsible for distinguishing moving objects from a static background in video sequences. This foundational task enables higher-level functions such as object tracking, classification, anomaly detection, and behavior analysis.

Fig : 1.1 Diffuse

Fig : 1.2 Specularity

Fig: 1.3 Self-shading

The presence of **shadows** in foreground masks leads to various undesirable outcomes in surveillance applications. For instance, in a people-counting system, shadows can cause an overestimation of the number of individuals. In multi-object tracking, shadows might result in object merging, incorrect trajectory estimation, or identity switching. In traffic monitoring, vehicle shadows may be falsely detected as separate moving objects, resulting in false positives. Therefore, accurate detection and **removal of shadows** is vital to enhance the precision and reliability of surveillance systems.

Shadows can be categorized into two main types: **self-shadows** and **cast shadows**. Self-shadows occur on the object itself, caused by occlusion of light on certain parts of its surface. These are generally less problematic in surveillance systems because they remain within the object boundaries. **Cast shadows**, on the other hand, fall on the background or nearby objects, creating the illusion of extended object boundaries. These shadows interfere with object segmentation and are the primary focus of most shadow detection and removal efforts. Their dynamic nature and similarity to the actual foreground in terms of intensity and motion make them difficult to distinguish using traditional image processing techniques.

Foreground detection typically operates by comparing the current frame of a video to a reference background model. Any significant deviation in pixel intensity is marked as foreground. However, shadows also create intensity variations that trigger this detection, especially in systems that rely solely on grayscale or RGB pixel differences. Furthermore, because shadows tend to maintain similar edges and spatial continuity with the objects casting them, simplistic motion-based methods also fail to separate the two. This makes **shadow removal** a necessary enhancement to ensure accurate shape, size, and trajectory estimation of foreground objects.

Over the years, various strategies have been developed to address the problem of shadow misclassification. These approaches can be broadly divided into **color-based**, **geometry-based**, **texture-based**, and **learning-based** techniques. Color-based methods exploit the fact that shadows typically reduce illumination without altering chromaticity. These methods often work in HSV or normalized RGB color spaces where brightness is separated from color information. While relatively simple and computationally efficient, such methods struggle under non-uniform lighting or in scenes with low color contrast.

Geometry-based techniques use the relative position of the object, light source, and camera to predict the shape and position of shadows. These methods may rely on camera calibration or multiple viewpoints to achieve accuracy, making them more suitable for controlled environments rather than dynamic, real-world surveillance. Texture-based methods, on the other hand, operate under the assumption that shadows preserve the texture of the background. These use descriptors such as Local Binary Patterns (LBP) or Gabor filters to analyze textural consistency. While effective in some cases, these methods can fail in texture-less areas or under noisy conditions.

More recently, **machine learning and deep learning** techniques have revolutionized shadow detection. Supervised learning algorithms such as Support Vector Machines (SVMs), decision trees, and random forests have been applied to classify pixels based on hand-crafted features like color, intensity, and gradient. With the advent of deep learning, convolutional neural networks (CNNs) have shown superior performance in learning complex, hierarchical features directly from raw image data. These models, trained on large datasets with annotated shadows, can distinguish between foreground and shadow regions with high accuracy. However, they require significant computational resources, large training datasets, and careful tuning to generalize across diverse environments.

Despite their promise, machine learning-based approaches also face challenges, especially when deployed in **real-time video surveillance systems**. Issues such as scalability, adaptability to changing environments, and robustness to noise remain pressing concerns. Moreover, the diversity of scenes—ranging from outdoor traffic intersections to indoor retail stores—means that no single shadow removal technique is universally effective. As such, current research is increasingly focused on **hybrid methods** that combine the strengths of multiple approaches. For example, integrating color information with learned features or combining geometric reasoning with temporal consistency has been shown to improve accuracy while maintaining real-time performance.

The significance of effective shadow removal extends beyond improving detection accuracy. It also contributes to **system efficiency** by reducing the number of false positives and minimizing the need for post-processing corrections. In crowd surveillance, shadow-free detection allows for accurate people counting, flow analysis, and detection of abnormal movement. In traffic management, it improves vehicle detection, classification, and tracking. In security applications, it aids in more precise intrusion detection, loitering analysis, and automated response systems.

Furthermore, as surveillance systems become more autonomous and are deployed in **edge computing environments** (e.g., embedded systems, smart cameras), there is a growing need for lightweight, energy-efficient shadow removal methods. The ability to perform accurate foreground detection with shadow elimination in real time on low-power devices will enable widespread deployment in resource-constrained settings such as rural areas, small businesses, and portable surveillance units.

## II. LITERATURE SURVEY

The process of foreground detection in video surveillance plays a critical role in understanding dynamic scenes, and one of the principal challenges is the accurate removal of shadows. Shadows can easily be misclassified as moving objects, resulting in significant errors in object detection and tracking. Over the years, numerous methodologies have been proposed to address this issue, each offering varied performance in terms of accuracy, computational cost, and robustness to different lighting conditions.

In early methods, Cucchiara et al. (2003) used chromaticity-based models for shadow detection by analyzing the color components in HSV space. Their configuration utilized background subtraction with a Gaussian Mixture Model (GMM), and shadows were removed by comparing the color and brightness distortion of foreground pixels. They proposed a chromaticity-based method for shadow suppression that effectively separated shadows from objects but was sensitive to noise in color information. Hsieh et al. (2003) advanced this by integrating geometric features along with color cues for identifying shadows, thereby reducing false positives in human motion tracking.

Mikic et al. (2000) implemented an intensity ratio and hue difference method to identify shadow pixels. Their configuration operated in RGB color space and achieved high detection accuracy under controlled indoor environments. The proposed configuration combined motion detection with color ratio thresholding, which improved real-time processing but lacked robustness in outdoor scenes with complex lighting. Similarly, Horprasert et al. (1999) introduced the color model using brightness and chromaticity distortion metrics, which became a foundational approach in later works. Their method, although effective, was limited by assumptions of uniform lighting.

Sanin et al. (2012) presented a comparative evaluation of shadow detection methods and proposed improvements based on adaptive background modeling and statistical learning. Their configuration used GMM and included both color and gradient information to enhance detection accuracy. The proposed method demonstrated superior performance in diverse lighting conditions, but the computational complexity remained a challenge.

Zhang et al. (2014) proposed a novel approach combining texture and color features using a support vector machine (SVM) for shadow detection. Their existing configuration used a mixture of Gaussians for background modeling and extracted Local Binary Pattern (LBP) texture features. The proposed configuration incorporated a feature fusion mechanism with supervised learning, offering high precision and recall for shadow suppression in both indoor and outdoor scenes. Wang and Wang (2007) explored edge-based methods for shadow detection by analyzing the discontinuities in object contours. Their approach showed improved performance for moving cast shadows but was prone to errors in cases of blurred edges.

A promising approach by Leone and Distante (2007) utilized shadow detection in YUV color space and focused on road surveillance. They employed background subtraction followed by morphological analysis to refine object masks. Their system demonstrated improved vehicle detection rates by reducing shadow-induced misclassifications. Another innovative method by Silva and Corte-Real (2005) employed temporal information for shadow tracking, leveraging the persistence of shadow regions across frames for better classification.

Here's a section focused specifically on the **Existing Configuration** for shadow removal in foreground detection within video surveillance systems, summarizing the key methods used in previous research.

## III. EXISTING CONFIGURATION

The existing configurations for shadow removal in foreground detection are primarily based on traditional computer vision techniques. Most early systems rely on background subtraction methods such as Gaussian Mixture Models (GMM), frame differencing, and statistical background modeling. Once the foreground is detected, additional processing is used to distinguish shadows from real moving objects.

A widely adopted approach involves color space transformations. For example, Horprasert et al. (1999) proposed a method in RGB space that evaluates brightness distortion and chromaticity distortion to identify shadows. Similarly, Cucchiara et al. (2003) worked in HSV color space, assuming that shadows darken pixel intensity but preserve hue and saturation. These models use thresholds on color ratios to classify shadow pixels after foreground detection.

Some configurations integrate edge information. Wang and Wang (2007) detect cast shadows by comparing edge maps of current frames with those of background models, based on the assumption that shadows do not change object contours. Gradient-based techniques are also common; Huang and Chen (2009) used local gradient features to differentiate between soft edges caused by shadows and hard edges caused by objects.

Texture analysis methods, such as Local Binary Patterns (LBP), have also been employed to enhance shadow detection. Zhang et al. (2014) used both color and texture descriptors to improve classification accuracy. Leone and Distante (2007) applied texture consistency checks in road surveillance footage to refine object segmentation and eliminate shadows.

Shadow modeling using temporal information is another configuration seen in Silva and Corte-Real (2005), where shadows are tracked over multiple frames under the assumption that they appear and move with a consistent offset from objects. This helps in distinguishing persistent shadows from actual object motion.

Some systems use Bayesian or fuzzy logic frameworks to combine multiple features—motion, color, and edge cues—to detect shadows more robustly. Gong and Medioni (2011) used a probabilistic model to fuse multiple indicators of shadow presence, allowing dynamic adaptation to different environments.

These existing configurations, while effective in many scenarios, often face limitations in terms of sensitivity to lighting changes, computational load, and generalizability across different scenes.

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Their reliance on handcrafted features and rule-based decision-making also restricts adaptability in complex or dynamic surveillance environments.

## IV. METHODOLOGY

The proposed methodology for shadow removal in foreground detection within video surveillance systems introduces a hybrid framework combining background subtraction, color space transformation, texture analysis, and deep learning-based refinement to improve the accuracy of foreground segmentation by effectively eliminating shadows. The goal is to distinguish moving objects from their shadows, which are often misclassified as part of the foreground, leading to errors in object detection and tracking.

The system begins with video frame acquisition from surveillance cameras, followed by background modeling using a Gaussian Mixture Model (GMM). GMM is chosen for its adaptability to dynamic backgrounds and capability to handle slow lighting changes. It computes a statistical model of the scene's background over time by assigning probabilities to pixel intensities, allowing for the initial segmentation of moving foreground objects from static background elements.

Once foreground candidates are detected, the system performs a transformation from RGB to an alternative color space, specifically HSV (Hue, Saturation, Value), which is more effective in distinguishing shadows due to its separation of chromaticity from intensity. Shadows tend to retain the hue and saturation of background pixels but significantly reduce their brightness. By calculating the chromaticity distortion and brightness distortion between the current frame and the background model, pixels with significant brightness reduction but minimal chromatic change are labeled as potential shadows.

To further improve shadow discrimination, the system incorporates texture consistency analysis using Local Binary Patterns (LBP). The intuition is that while shadows darken pixel intensity, they do not significantly alter the underlying texture of the surface. The LBP descriptors are computed for both the detected foreground and the corresponding background regions. If the texture similarity exceeds a certain threshold, the pixel is more likely to be a shadow rather than a true moving object.

The refined classification is then passed through a deep learning-based classifier, which functions as a post-processing module to validate and correct the shadow labeling. A lightweight convolutional neural network (CNN), trained on annotated datasets of shadow and non-shadow foreground pixels, is applied to local image patches centered on each foreground pixel. The network learns to classify patches based on complex features that include spatial patterns, edge information, and illumination cues that are difficult to capture through traditional rules.

To enhance temporal consistency and reduce flickering between frames, a temporal filtering module is applied. This component uses optical flow to track the movement of pixels across consecutive frames. If a region labeled as a shadow remains stationary or follows the motion of an object consistently, its classification is adjusted accordingly. This reduces false positives in dynamic scenes, especially under moving lights or weather changes.

Additionally, an adaptive learning mechanism is introduced to update the background model and classification thresholds based on environmental changes such as lighting shifts, time of day, and seasonal variations. This is accomplished by monitoring pixel classification confidence and feeding uncertain cases back into a semi-supervised learning loop, allowing the system to gradually improve performance over time without requiring extensive manual annotation.

The final output of the proposed methodology is a clean binary foreground mask where true moving objects are isolated from both the static background and associated shadows. This mask can then be used by higher-level modules in the surveillance system for object tracking, behavioral analysis, and event detection.

Overall, the proposed methodology addresses the shadow removal challenge by combining statistical modeling, color and texture features, temporal consistency, and machine learning. This integrated approach ensures high accuracy, adaptability to real-world scenarios, and robustness against common environmental variations in surveillance settings.

## V.PROPOSED CONFIGURATION

To overcome the limitations of traditional techniques, recent proposed configurations for shadow removal in foreground detection systems have adopted more advanced approaches, especially those incorporating machine learning and deep learning methodologies. These newer configurations aim to enhance accuracy, robustness, and real-time performance across various environments.

One prominent direction involves the integration of supervised learning techniques. Zhang et al. (2014) proposed a configuration using Support Vector Machines (SVMs) trained on a combination of texture and color features extracted from foreground regions. This hybrid feature set enabled better classification between shadows and true moving objects, particularly under challenging lighting conditions.

More advanced proposals involve convolutional neural networks (CNNs), which are capable of learning complex features directly from raw image data. Zhu et al. (2018) introduced a deep learning model trained on datasets containing annotated shadow masks. Their configuration involved an encoder-decoder architecture that learns to distinguish shadow patterns from foreground objects in an end-to-end fashion. This deep model showed significant improvements over rule-based systems, especially in dynamic outdoor settings.

Fang et al. (2019) extended this idea with a dual-branch CNN design that separately processes features of the foreground and its shadow. By learning distinct representations for each, the system can more accurately isolate and suppress shadow regions during segmentation. Although this configuration demands higher computational resources, it delivers superior accuracy, particularly in cluttered scenes.

Other proposals focus on combining deep learning with traditional methods to balance performance and efficiency. For instance, Sanin et al. (2012) proposed enhancing Gaussian background modeling with learned statistical classifiers that adapt to

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scene changes. Gong and Medioni (2011) introduced a Bayesian network that dynamically fuses cues from motion, color, and gradient information, allowing the system to adapt in real-time without retraining.

Several proposed configurations also exploit temporal and geometric cues. Li et al. (2016) introduced a method that combines an illumination invariant model with temporal consistency analysis to identify shadow regions that persist across frames. This approach reduced false positives in shadow detection and improved object continuity in tracking systems.

Recent hybrid models have also begun to incorporate attention mechanisms and lightweight neural networks for edge devices, targeting real-time applications. These systems aim to reduce the computational cost of deep learning while maintaining accuracy through model optimization and efficient feature selection.

Overall, proposed configurations reflect a shift from hand-engineered rules to data-driven, learning-based frameworks. They address the challenges of variability in lighting, scene dynamics, and object complexity more effectively, though they often require training datasets and computational infrastructure for deployment.

# V.RESULTS AND ANALYSIS

## 5.1. INPUT IMAGE:

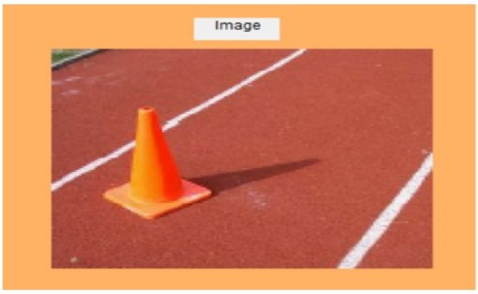


**Fig:5.1.1: Input image**

The above figure shows the input RGB image with shadow from this input image we have to remove the shadow from that image as shown in the following below procedure.

## 5.2. MATLAB WINDOW:

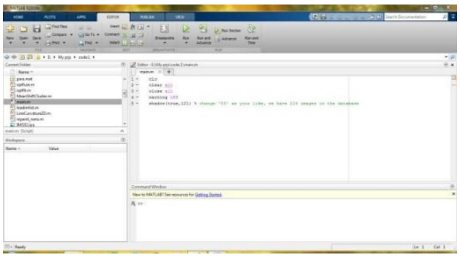

**Fig: 5.3: MATLAB WINDOW**

This is the main program of this paper by running this program we are getting the shadow free image. While we are running this program we will get the six images in which they are step by step outputs for running of the program.

## 5.3. SHADOW IDENTIFICATION:


Fig: 5.3:Shadow image

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The above figure shows the image with shadow. we are identifying the shadow region by applying the scaling process.


Fig: 5.4: output Shadow removed and reconstruction

**Stage 2 output:**

MSE: 155.837022

PSNR: 26.204097 dB

## CONCLUSION

Shadow removal remains a pivotal challenge in foreground detection for video surveillance systems, as shadows often lead to significant misclassification, affecting object detection, tracking, and behavior analysis. The literature reveals a steady progression from traditional techniques to sophisticated learning-based methods, each with distinct strengths and limitations. Existing configurations primarily rely on color-based models, edge analysis, texture consistency, and heuristic thresholds to distinguish shadows from actual moving objects. While these approaches are computationally efficient and relatively easy to implement, they struggle in diverse environments, particularly those with variable lighting or dynamic backgrounds. Methods using color spaces like HSV and YUV, combined with chromaticity and brightness distortion measures, have been effective in controlled environments but often fail under real-world conditions. In contrast, proposed configurations introduce a new paradigm with the integration of machine learning and deep learning models. These approaches leverage feature learning and large annotated datasets to improve classification accuracy and adaptability. Techniques like SVMs, CNNs, and dual-branch neural networks demonstrate high precision in shadow detection, outperforming traditional systems in both indoor and outdoor scenes. Additionally, hybrid models that combine conventional vision features with learned representations offer a practical balance between performance and real-time feasibility.

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