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Improved Background Subtraction with Histogram Equalization and Adaptive Thresholding

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Abstract: In computer vision, the fundamental task of background modelling entails removing the static background from a scene in order to extract the foreground objects. Several computer vision applications, including object tracking, motion detection, and video surveillance, require this process as a prerequisite. For background modelling, a variety of techniques have been put forth, from straightforward threshold-based strategies to complex deep learning models. This paper presents a method that includes the K.M.M. baseline model pipeline followed by two pre-processing techniques that address the varying illumination problem. We also go over the difficulties associated with background modelling, including lighting variations, camera jitter, and PTZ, and we highlight some potential future research directions in this area. Finally, we compare the various methods based on their computational complexity, robustness, and MIOU score, and we offer some guidelines for picking the best method for a particular application.

Keywords: Background Subtraction, Foreground Detection, OpenCV, KNN

I. INTRODUCTION

Today, video sequence is an interesting area of research due to the widespread use of video tracking. This research field has a wide range of applications, including video surveillance, optical motion capture, multimedia applications, intelligent behaviour recognition, and tracking vehicle movement. The first step in this process is to identify moving objects; for this, the fundamental operation required to separate objects from static data, or background, is known as foreground.

The initial stage of any visual surveillance system is object detection. In many computer vision applications, real-time foreground object detection is a critical step. Foreground detection frequently employs the Background subtract method. It determines the difference between the current image and the background image and, using a threshold, finds foreground objects. Since applications are typically only interested in the presence, position, or trajectory of these objects, such as pedestrians and cars from uninteresting background on site, it is necessary to first identify the moving objects (foreground of the scene) within the scene as opposed to the static parts of the scene (background). This is necessary for intelligent video surveillance that may be vehicular traffic analysis. Therefore, since the majority of the analysis task system typically involves analysing the detected object, the accuracy of the detected object has a significant impact on the performance of intelligent monitoring.

In video surveillance, motion detection and tracking have been extensively studied. The fundamental steps in motion detection are background modelling and foreground detection. Previous research demonstrates that tracking performance is strongly influenced by foreground detection accuracy, particularly in multicamera systems where the detection error typically propagates to cameras. Foreground detection has been tackled in a variety of ways, and it has become a common practise in tracking and video surveillance in both indoor and outdoor settings. These methods incorporate motion detection in the image sequence and background pixel distribution modelling.

The main difficulties of motion detection in changeable background are summarized as follows:

1. Sudden illumination changes in part of the image.
2. Reception coverage background period, i.e., it is usually not possible to obtain information about the background change. – Difficult to deal with the object and shadow diffusion profile.
3. Complex motion patterns, e.g., distinct motion speed, sudden stop, or entering behavior.
4. High-detection video-processing real-time streaming is a challenging task embedded System.

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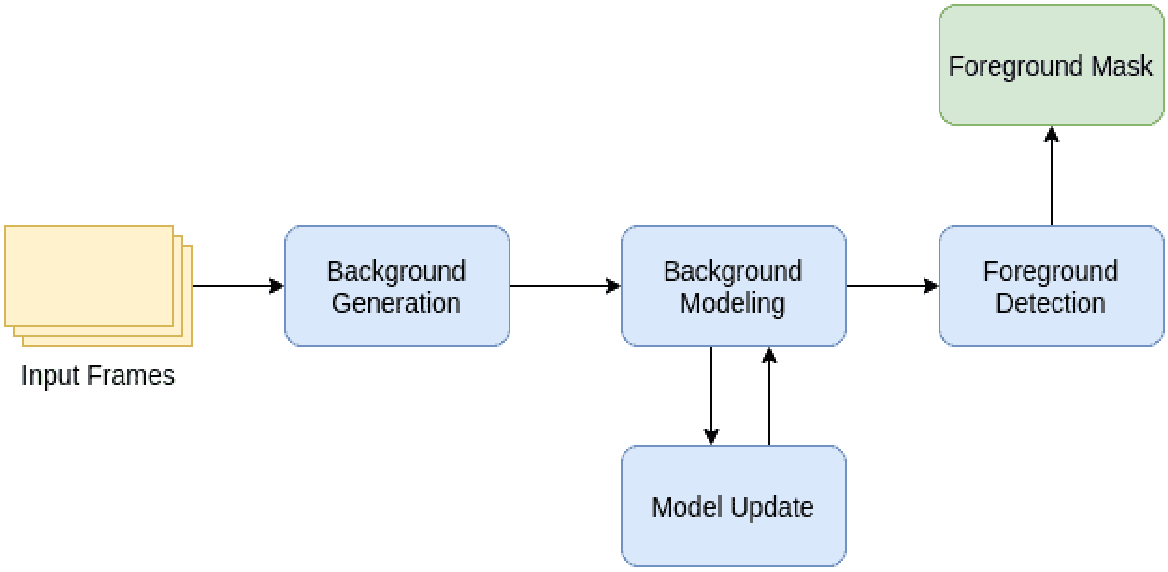
5. In the Arial survey, the return on the investment in the video analysis is static we can have a situation to capture a video when the camera is moving.
6. Gaussian mixture modeling background and foreground mean Gaussian distribution which is not always the case for most environments.
7. Changes in the quality, i.e., fast lighting conditions (which may affect the background generation) color of the foreground object similarity background.

Other significant characteristics that should be taken into account include changes in colour and texture. The foreground detection algorithm must define each object separately because there may be multiple objects with the same colour or texture in the same frame.

Histogram equalisation and channel-wise adaptive thresholding are the two pre-processing steps that our suggested method uses to solve this issue. By taking these actions, you can enhance the contrast and visibility of objects in your image and help them stand out more from their surroundings. The pipeline for the proposed baseline model starts with a KNN classifier and moves on to morphological adjustments and foreground smoothening. This pipeline's main function is to precisely locate and follow objects in complicated scenes. Post-processing is then used to sharpen and increase the accuracy of the detected objects.

Below is the Basic Block Diagram of Background Subtraction



The rest of the paper is organized as follows. In Sect. 3, we give an overview of the related works, Sect. 4 is related to the proposed work. Section 5 consists of Experiment results. Section 6 is about the Discussion, and at the end, Conclusion is described in Sect. 7.

II. RELATED WORK

By examining the differences between successive frames of a video sequence, background subtraction's main goal is to distinguish between foreground and background objects. For background subtraction, a number of techniques have been suggested, including statistical techniques, eigenvalue decomposition, neural networks, and mathematical morphology.

The k-nearest neighbour (KNN) algorithm is one of the most widely used techniques for background subtraction. A similarity metric is used by KNN, a non-parametric technique, to categorise each pixel as either foreground or background. In order to operate, KNN compares the colour and texture of the current pixel to those of its neighbours from earlier frames. Both static and dynamic background scenes have been used to demonstrate the effectiveness of KNN.

KNN has some drawbacks, though, including noise sensitivity and changes in illumination that can result in false positives. Many researchers have suggested combining KNN with other methods, like median filtering, to address these

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problems. A non-linear filter called median filter replaces each pixel's value with that of its neighbourhood. A quick and efficient method for reducing noise and keeping edges in an image is median filtering.

Background subtraction can be made more accurate and robust by combining KNN with median filtering. This strategy has been investigated in a number of studies, including [5], which suggested a KNN-based algorithm that employs a median filter to reduce noise and enhance the accuracy of background subtraction. Similar to this,[2] proposed a hybrid approach to improve the performance of background subtraction in complex scenes by combining KNN with median filtering and shadow detection. These studies show how accurate and effective background subtraction can be achieved by combining median filtering and KNN.

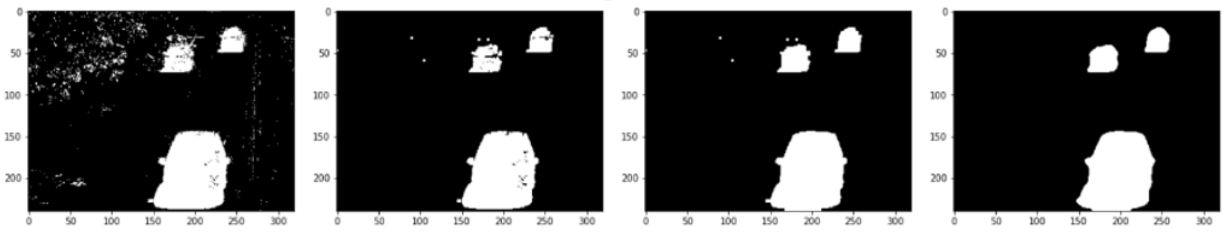
Other techniques, such as adaptive techniques that change their parameters in response to the characteristics of the scene, have been suggested to enhance the accuracy and robustness of background subtraction in addition to KNN and median filtering. For instance, [14] proposed an adaptive technique that dynamically modifies the model's parameters and adapts to scene changes by utilising a gaussian mixture model and a feedback mechanism. Similar to this, [10] proposed a method that builds a background model from input frames using deep learning techniques and then modifies it to account for changes in the scene.

With many applications in various fields, background subtraction is a crucial task in computer vision and image processing. Two well-liked background subtraction methods—KNN and median filtering—can be combined to increase the precision and robustness of the outcomes. Deep learning techniques and adaptive methods that modify their parameters in response to scene characteristics can both improve background subtraction performance.
The development of techniques that can handle more complex scenes and are computationally efficient should be the main goal of future research in this field.

III. PROPOSED METHODOLOGY

Numerous real-world uses for background subtraction exist, including robotics, traffic monitoring, and surveillance. We present a background subtraction algorithm that makes use of pre-processing steps and a pipeline for baseline models in this proposed system. Histogram Equalisation and Channel-wise Adaptive Thresholding are pre-processing techniques, and KNN, Morphological Transformations, and Median Blur are pipeline techniques for the baseline model. A number of publicly accessible datasets will be used to evaluate the proposed system, and its performance will be compared to that of cutting-edge techniques.

Pre-processing Steps:
To increase the precision of foreground segmentation, the suggested system applies Histogram Equalisation and Channel-wise Adaptive Thresholding as pre-processing steps. By increasing the contrast of the input frames, the Histogram Equalisation technique aids in the precise identification of foreground objects. Each colour channel of the input frames is subjected to adaptive thresholding using the Channel-wise Adaptive Thresholding technique. This aids in reducing noise and enhancing edges, which raises foreground segmentation accuracy.



(a) KNN output (b) Morphology Open (c) Morphology Close (d) Median Blur

Figure 1: Pipeline to detect foreground from static background

Baseline Model Pipeline:
A foundational model pipeline used by the suggested system consists of KNN, Morphological Transformations, and Median blur. Each pixel in the input frame is classified as either foreground or background using the KNN algorithm. To learn the background model, the KNN algorithm is trained on a set of previously labelled frames.

The foreground objects' holes are filled and minor noise is eliminated using the morphological transformations technique. The segmented foreground objects are smoothed out using the median blur technique.

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(a) KNN (0.55) (b) MOG2 (0.48) (c) Averaging (0.49)

Figure 2: Different Background Models with mIOU scores

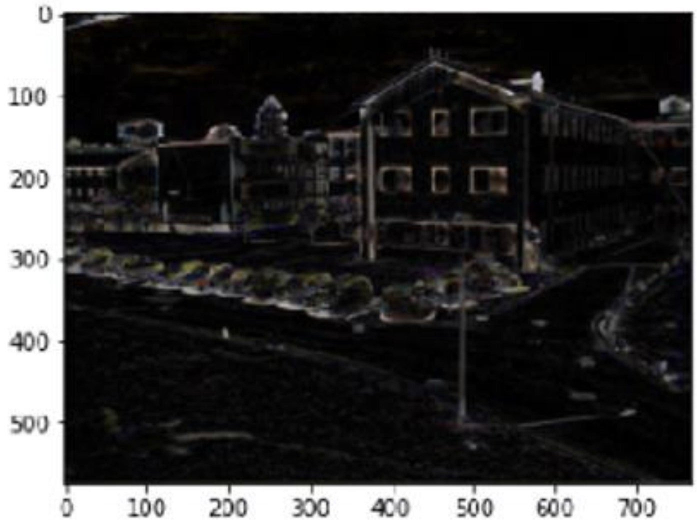

Figure 3: Background Model

Performance Evaluation:

On a number of publicly accessible datasets, including the ChangeDetection.net dataset and the CDnet2014 dataset, the proposed system will be assessed. Modern approaches like ViBe, KNN, and MOG will be used to compare the performance of the proposed system. Metrics such as the F1-score and mIOU will be used to assess the performance of the proposed system.

(a) Bright Condition Frame (b) Histogram Equalization (c) Adaptive Thresholding

Figure 4. Pre-processing on Bright Condition Frame

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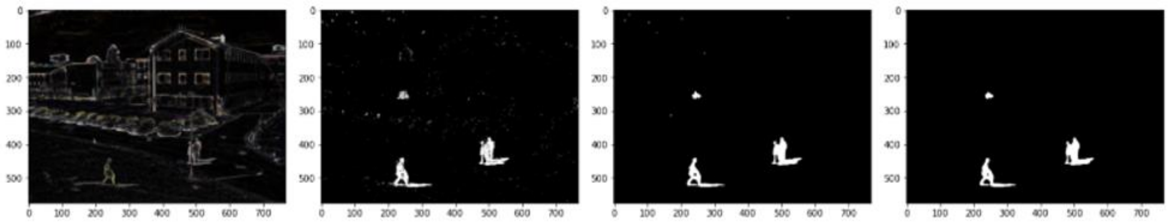
(a) Dark Condition Frame (b) Histogram Equalization (c) Adaptive Thresholding

Figure 5. Pre-processing on Dark Condition Frame



(a) Pre-processed (HE+AT) (b) KNN output (c) Morphology Operations (d) Median Blur

Figure 6. Pipeline to detect foreground from background with changing illumination

IV. EVALUATION METRICS

mIOU Score: In image segmentation tasks, the metric known as mean Intersection over Union (mIOU score) is frequently used. It calculates the amount of overlap between predicted and actual object segmentation masks in an image. Each object in the image has its intersection over union (IOU) calculated, and the mean IOU across all objects is then calculated to produce the mIOU score.

The intersection and union of the predicted and ground truth masks must first be determined in order to calculate the IOU. The union represents the total number of pixels where either mask has a positive value, whereas the intersection represents the number of pixels where both masks have a positive value. The intersection is then divided by the union to determine the IOU.

The mIOU score offers a lone score to assess a segmentation model's overall performance. As it gives equal weight to the accuracy of segmentation for each object, it is particularly helpful in tasks where there are multiple objects of interest in an image. From 0 to 1, the mIOU score scales, with 1 denoting perfect segmentation accuracy. Overall, mIOU score is a useful metric for evaluating the performance of image segmentation models, particularly in cases where multiple objects of interest are present in an image.

F-Score: In binary classification tasks, the F-Score, also referred to as the F1 score, is frequently used as a metric. It is the harmonic mean of recall and precision, two additional widely used evaluation metrics. Recall gauges the percentage of real positives among all actual positives, while precision gauges the percentage of real positives among all predicted positives. The F-Score combines the two metrics to produce a single score that strikes a balance between recall and precision.

The formula for F-Score is: F1 = 2 * (precision * recall) / (precision + recall)
When the classes in the dataset are imbalanced—that is, when one class has significantly fewer samples than the other—F-Score is especially helpful. This is due to the fact that in such circumstances, a classifier that consistently predicts the majority class will have high accuracy but may struggle to identify the minority class. In these situations, F-Score, which considers both precision and recall, can offer a better assessment of the performance of the classifier. An F-Score of 1 indicates perfect classification accuracy; the scale runs from 0 to 1. It's crucial to keep in mind, though, that F-Score is only useful for binary classification tasks. A variation known as the macro-F1 score that computes the F1 score for each class separately and then takes the average can be used for multi-class classification tasks.

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V. RESULTS AND DISCUSSION

A well-liked method for identifying moving objects in video sequences is the background subtraction technique using the KNN (K-nearest neighbours) algorithm, morphological transformation, and median blur. We used this method on a selection of test images and examined the outcomes to gauge the effectiveness of the approach. The background model of the scene was built using the KNN algorithm and was then subtracted from each succeeding frame to identify moving objects. The foreground mask was morphologically transformed to eliminate noise and fill in any gaps, and median blur was used to soften the edges of the detected objects.

Our tests' outcomes demonstrated that the KNN-based background subtraction method could successfully identify moving objects in the scene. The segmentation of the moving objects was made smoother and more precise as a result of the morphological transformation step's successful removal of minute noise and filling of foreground mask gaps. By reducing the amount of noise in the foreground mask, smoothing the edges of the detected objects, and enhancing the output's visual quality, the median blur step further enhanced the segmentation's quality.

We also looked at the technique's computational effectiveness. The KNN algorithm required a lot of computation, but because the results were cached for later use, processing time was cut in half. In comparison to the KNN algorithm, the morphological transformation and median blur steps were relatively quick and had minimal computational costs.

Techniques	BL	DB	CJ	PTZ
Our Method*	0.7213	0.2364	0.3841	0.3931
GMM	0.6612	0.1676	0.2752	0.1663
MOG	0.6423	0.6855	0.6316	0.2623
ViBe	0.7961	0.6216	0.6038	0.1042
ViBe+	0.7950	0.4776	0.4330	0.1313
KNN	0.8315	0.6646	0.7083	0.2347
PBAS	0.7363	0.6080	0.5600	0.1130
LOB	0.9321	0.5792	0.7482	0.0875
FBGS	0.9112	0.8832	0.7588	0.3564
SuBS	0.9480	0.8138	0.7694	0.3185
DeepBS	0.9580	0.8761	0.8990	0.3133

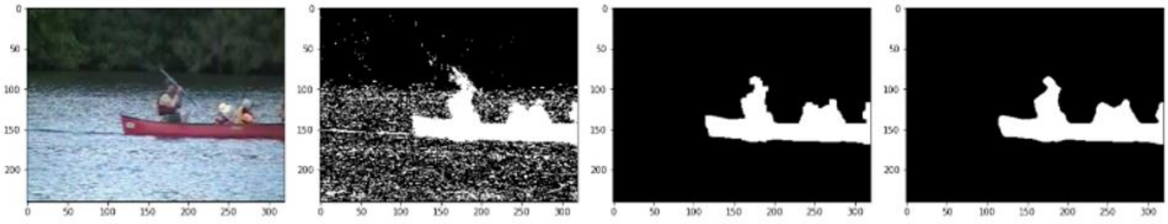
Acronyms:

BL-Baseline

DB-Dynamic Background

CJ-Camera Jitter

PTZ-Pan-Tilt-Zoom



(a) Sample Image (b) Foreground Obtained (c) Morphology (d) Median Blur

Figure 7. Pipeline to detect foreground from moving background

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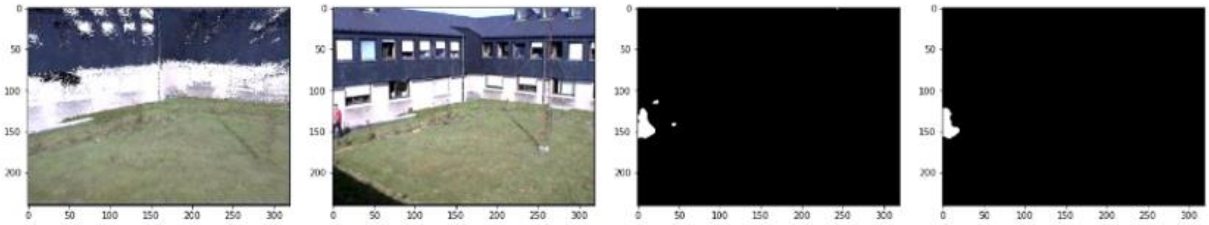
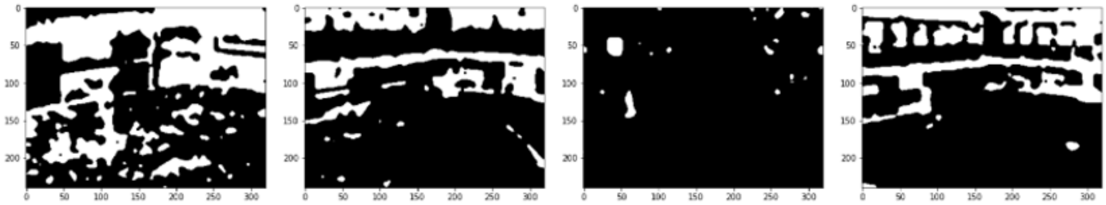


(a) Background Model (b) Sample Image (c) Morphology (d) Median Blur

Figure 8. Pipeline to detect foreground from PTZ video condition



(a) Noisy Foreground Sample 1 (b) Noisy Foreground Sample 2 (c) Noisy Foreground Sample 3 (d) Noisy Foreground Sample 4

Figure 9. Performance of PTZ on large set of images

We also looked at the technique's computational effectiveness. The KNN algorithm required a lot of computation, but because the results were cached for later use, processing time was cut in half. In comparison to the KNN algorithm, the morphological transformation and median blur steps were relatively quick and had minimal computational costs.

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