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Original Article

Area Efficient Moving Object Detection using Spatial and Temporal Method in FPGA

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Abstract - *Background subtraction has become a challenging task for moving objects. Mainly its complexity of implementation at moving background. Area Efficient hardware implementation of a moving object detection algorithm using FPGAs is described in this paper. The algorithm aims to remove moving items' backgrounds from the CDNet dataset. Even though occlusions aren't detected, simple shadow and highlight reduction are performed. The technique is best implemented on pipelined technology and is optimized for high frame rates. The authors proposed unique improvements, such as background binary mask combinations or non-linear functions in highlight detection, which improved the resiliency and efficiency of hardware implementations. After being developed in FPGA, the method was tested on the CDNet dataset.*

Keywords - *Binary Mask, BS, CDNet, FPGA, GMM, etc.*

1. Introduction

In theory, background extraction entails identifying pixels that remain static for a set amount of time and belong to stationary objects, as opposed to pixels that have large fluctuations and belong to moving objects. In recent years, a slew of new background subtraction (BS) algorithms have been created, and nearly all of them have shown to be successful. It can range from simple algorithms with low performance to more robust ones with better performance. Algorithms with a high computational cost are frequently unsuitable for real-time applications (applications that operate in a time that the user perceives as actual). Several approaches have been identified in the literature. They can be categorised based on their goals (statistical representations, intensity) that is used to model the background, among other things), the adaptation strategy (recursive, predictive) or the (pixel-level, region-level, frame-level) image element [1].

Motion detection aims to identify the physical movement of an object within a specific region or area. By assuming that the only difference between the background image and the current frame is the existence of moving objects, background subtraction attempts to locate this motion (foreground). As a result, the movement areas can be derived by simply subtracting the background from the current frame and thresholding the difference. Background subtraction should ideally meet the following conditions to complete this task:

- The camera is stationary, and its settings are set. Otherwise, any pixel alterations in the current frame caused by these events could be deemed foreground.
- Because changing the pixel intensities would affect the background, there are no fluctuations in illumination on the scene or directing lights that form shadows.
- There is no movement in the background. Over time, background objects are neither shifted nor introduced.
- There are no foreground objects in the previously static background image.

The background subtraction models aim to increase speed while lowering memory needs. It represents the background (B) by computing the average, mean, or median image of the input sequence, which frequently does not contain moving objects. The new frame (I_t) is then subtracted from the background model image at each time (t), and the result is thresholded using a threshold value (Th) to identify a pixel as background or foreground [2] [3].

$$|(I_t) - B| > Th \qquad (1)$$

Other algorithms utilize dynamic thresholds per pixel since the background pixels vary dynamically, and a weak static threshold might result in poor segmentation [4] [5].

By iteratively updating the model using adaptive filters, this type of model can adapt to slow illumination changes in the scene. However, in real-world outdoor applications, the scene's background incorporates several non-static elements (dynamic background), such as tree branches and plants, which move in response to the wind. Because of the dynamic background, the pixel intensity values change dramatically over time. The basic models for pixel intensity/colour would not hold in this multi-modal intensity distribution, and overall accuracy would be low [6].

Enhanced background estimations have been made possible by combining numerous models to create complementary approaches that improve the quality and accuracy of detection results. For example, the authors of [7] showed that combining a background estimation strategy for motion detection in non-static backgrounds with an improved background estimation method employing a short-term and long-term model improves the quality and reliability of the detection findings. The authors of [8] suggested a BS technique that uses center-surrounded computations to assess local feature saliency and considers biological vision to define local saliency. The innovative BS method, suggested by the authors of [9], is extremely efficient in complex situations. There are two parts to this process: foreground detection and foreground refining. The first considers the background pixel a collection of adaptive phase features. In the meantime, to aggregate the pixels surrounding the foreground, the second one uses the distance transform to make the end effect clearer and more integrated. Colour, location, and temporal coherence models are learned in the same environment. The authors of [49] combined several different techniques. The model was built using the parametric pixel-level GMM model and the nonparametric regional KDE model. The background colour dispersion is learnt from pixels from the previous frame's neighbours, while the foreground colour distribution is learned from pixels from the previous frame's neighbours. Finally, there are background and foreground distributions by location. The nonparametric model KDE is used to approximate the foreground. The Markov chain is employed to create a model of colour; colour, location, temporal coherence, and spatial coherence come next.

2. Literature Review

In period, different background subtraction algorithms have been introduced by various researchers. Pixel-oriented techniques [5] [11-14] determine the background or foreground models based on their pixel intensities. The Gaussian Mixture Model (GMM) [15], [16] is a traditional pixel-based scheme that represents each pixel as a Gaussian mixture model.

The GMM model is unable to describe pixels in the foreground effectively. Improved GMM claims to adjust the number of Gaussian components [17]–[19]; hence, the GMM model can dynamically adjust the scene. The local binary pattern (LBP) feature-based model was presented in [20] for feature-based background and performance by utilizing local dependencies between adjacent pixels. Additionally, neural network-based methods [21] have been created to adaptively train the background model and handle various illumination and moving backgrounds. Pixel-based algorithms, notwithstanding their efficiency, are typically dependent on assumptions learned from training datasets.

Furthermore, such techniques fail to describe global background image correlations between frames appropriately. In complicated environments, pixel-based models' performance is likely to deteriorate or even fail due to variations in illuminations and perspectives and the dynamic background. In the RPCA-based algorithms [22]–[27], every frame is represented as a column matrix in the 2D data matrix, which is subsequently decomposed into two matrices. The low-rank matrix represents background information, and the sparse matrix represents foreground information.

RPCA-based approaches have sparked a lot of interest since they can fully exploit the temporal correlations of the backgrounds.

The Robust Principal Component Analysis (RPCA) technique [28] was employed for background subtraction since the background images in different frames are considerably related. The authors of [29] simplify Gaussian models using each pixel's absolute maximum, lowest, and biggest consecutive difference values. The sensitivity of the moving object recognition can be increased by including colour information. Various colour models, such as RGB or HSV [30], can be used for this.

Gaussian distribution modelling of each pixel is insufficient to solve nonstationary backgrounds. To overcome that Mixture of Gaussians (MOG) [31-32] approach is proposed, in which a few regularly updated distributions define each pixel. The authors of [34] use a statistical model of gradients in conjunction with a tiered method for image analysis that encompasses; "pixel-level", "region-level", and "frame-level" processing. The authors of [35] describe an intriguing FPGA version of the improved MOG method (using off-chip RAM) that also adds hardware blob labelling.

Other methods have been found in the literature. A simple adaptive filter-based method to estimate the kernel density of pixels in [36], Kalman filter [37], is used to predict the background. Further, a linear prediction (Wiener filter) is used in stationary segmentation of the video frame, with an auto-regressive method of order 30 [48], mean-shift based estimation [39] is used by max and min value of background model, and Eigen backgrounds [40] using PCA is used frequently.

3. Proposed Methodology

3.1. Overview of Segmentation Module

Detecting moving objects is a current problem widely studied in computer vision [40-42]. Its applications are diverse, such as video surveillance systems and highway traffic monitoring. More recently, an application that has grown a lot is the multimedia applications developed in augmented reality, such as the animation of computational objects and motion-oriented video games.

Segmenting moving regions in the video, such as persons and cars, is important in detecting moving objects. The objects segmented in this step will be used as input information for the other modules of the system: monitoring and event management. Therefore, this step is crucial for the development of the proposed system. In a video, numerous methods for detecting moving regions/objects exist. This paper is accomplished using the background subtraction technique in this research.

This heading presents the methodology used in this work to segment moving objects in external environments using infrared images.

3.2. Background Subtraction

Among the various methods of segmenting moving objects found in the literature, this research work utilizes the background subtraction method to perform this task. The method was chosen because it does not depend on the scene type or origin environment. Furthermore, the background subtraction method's algorithmic complexity and execution speed are low, which justifies its use in the type of monitoring application proposed in this work.

To retrieve moving objects, the background subtraction approach involves calculating a reference image that is subtracted from the current image of the current frame. This reference image represents the background of the scene, or background, which evolves. As a result, an image representing the background is calculated for each video sequence frame. Moving objects may be removed from the scene using a threshold by comparing this reference image to the current frame image in the video series. The current image minus the background gives the foreground, in which the moving objects of the scene are contained.

To acquire the foreground image, most background subtraction methods compare the current image of the video stream with the estimated background image using a set threshold. On the other hand, this fixed threshold cannot adapt the background subtraction approach to abrupt changes in the scene, which are common in outdoor settings. As a result, this paper dynamically generates this threshold for each image in the video sequence to improve the segmentation of moving objects.

Inspired by what is proposed in [43], this research work utilizes a background subtraction technique that adapts to changes in scene lighting by utilizing a dynamic threshold, which makes the process of segmenting moving objects more robust. The idea of motion flow analysis in the segmentation process is introduced to improve the segmentation of small objects in the scene.

3.2.1. Calculation of the Foreground

The foreground is calculated using the difference between the background and the current frame of the video applied to a binarization threshold, and it contains the moving objects in the scene at a given moment k. Here, $FORE_k$ is constructed which is the foreground at instant k and represented by a binary image, checking whether or not each point (i, j) of F_k belongs to the foreground. $FORE_k$ is given by equation (2).

$$FORE_k(i,j) = \begin{cases} 1 & if\ |F_k(i,j) - Bg_k(i,j)| \geq Th_k \\ 0 & Otherwise \end{cases} \quad (2)$$

Where,

- $1 \leq i \leq N$
- $1 \leq i \leq M$
- Th_k is the applied binarization threshold that determines whether or not a pixel belongs to the foreground. It is calculated at each instant k and will be detailed later;
- F_k the frame at instant k;
- Bg_k the background of the scene at the time k;
- $FORE_k$ the foreground of the scene at time k;
- $1 \leq k \leq q$
- $F_{-l}, F_{-l+1}, F_{-l+2}, \dots, F_{-1}, F_0, F_1, \dots, F_q$ is a sequence of $(l + q + 1)$ frames of size $N \times M$, where the background initialization is done in the first l frames of this sequence.

The choice of binarization threshold is very important for the quality of the segmentation. Choosing a very high value can lead to the loss of significant parts of the detected moving object, and choosing a very low threshold can introduce noise in the segmentation, causing objects that do not object to appear (false positives), which can even make it impossible to detect the true target objects of the segmentation.

3.2.2. Calculation of the Background

Another problem in segmentation is that the scenes are from outdoor environments that constantly change (presence of constant movement, gradual changes in scene lighting, etc.), so updating the background is essential. For this, the research work applies a low-pass time that is defined by the equation (3):

$$Bg_{k+1} = Bg_k + \alpha_k(F_k - Bg_k) \quad (3)$$

Where,

- $0 \leq \alpha_k \leq 1$ is the dynamic learning rate;
- F_k is the image of the video sequence at instant k;
- Bg_{k+1} is the image background calculated at instant $k+1$;
- Bg_k is the image background calculated at time k.

By addressing gradual variations in brightness intensity and the existence of moving objects in the image, Equation (3) allows the system to adapt continuously to the scene background. The higher the value of α_k, the more changes in the scene will be incorporated into the background.

Outdoors, the sudden change in scene lighting can frequently happen (such as the alternating sun-cloud caused by wind). In this specific case, even with an optimal binarization threshold fixed in equation (2), the background subtraction technique can fail because the scene background adjustment speed when using a constant α_k, is unable to keep up with the speed of change in the scene. So that the equation (3) can be used and correctly estimates the background for each instant k, and first needed to initialize it, that is, calculate Bg_0. To do this task, this paper utilizes the first l frames of the video series and applies equation (4) to perform background initialization.

$$Bg_k = \begin{cases} F_k & if\ k = -l \\ Bg_{k-1} + 0.5(F_{k-1} - Bg_{k-1}) & Otherwise \end{cases} \tag{4}$$

Where $-l \leq k \leq 0$

3.2.3. Motion Segmentation Module Architecture

The problems mentioned above are often due to the poor quality of the captured infrared images and the inability of the background subtraction technique to adapt to sudden changes in lighting in outdoor environments.

One solution is to find a mathematical formula that uses temporal monitoring of changes in the intensity of gray-level image pixels caused by sudden changes in ambient lighting to adjust the binarization threshold and the scene background dynamically. Then compensate for the lack of information generated in the foreground calculation process using a suitable tool. This paper uses an algorithm proposed in [43] that combines background subtraction and ROI selection of segmented objects. A functional diagram of this model is shown in Figure 1.

As shown in Figure 1, motion segmentation is performed in two main steps: extracting a binary mask from the pixels belonging to the foreground and combining the object resulting from the first step with the corresponding edges of the original image. Finally, the segmentation is obtained through the application of morphological operations.

The difference between the method used in this work and other methods of background subtraction found in the literature is in the use of the threshold (equation (2)) and the learning rate (or gain, equation (3)) dynamically calculated for each frame of the video.

The system can swiftly react to sudden changes in illumination in the scene thanks to the dynamic adjustment of these parameters. This adjustment is made on every k frame of the video. For this calculation, the history of the temporal evolution of the average of the gray levels of the pixels of each sequence frame is used. Equation (5) defines the average of the gray levels of the k-frame pixels of the sequence

$$Mean_k = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} F_k(i,k)}{NM} \tag{5}$$

The size of the vector used to store the lighting variation history of the scene, $p+1$, must be chosen properly to accommodate the significant variations in the observed scene. The frame rate per second (FPS) of the video has a direct impact on the size of the video. The larger this vector is, the higher this rate is. The definition of this vector is shown below.

$$V = \left(Mean_{k-p}, \dots, Mean_k\right),\ \ k > p \tag{6}$$

Where $Mean_k$ represents the average intensity of gray levels of the frame's pixels at instant k.

3.2.4. Dynamic Threshold Calculations

Background subtraction-based motion segmentation quality depends primarily on choosing an optimal binarization threshold. But due to uncontrollable weather and lighting conditions, this choice is, on average difficult and problematic, as seen in applications that monitor outdoor scenes over a long time.

To deal with these conditions, it is necessary to automatically calculate an adaptive threshold that can adjust to any eventual change in the scene. Equation (7) may be used to automatically compute a dynamic threshold for each instant k of the video sequence using the history of the average grey levels of the pixels in the image.

$$Th_k = \beta(Mean_k + \Delta_k) \tag{7}$$

Where:

- Th_k: represents the value of the dynamic binarization threshold calculated at instant k;
- β: represents a value defined by the user. In proposed implementation, this value is in the range $[0.1, 0.5]$;

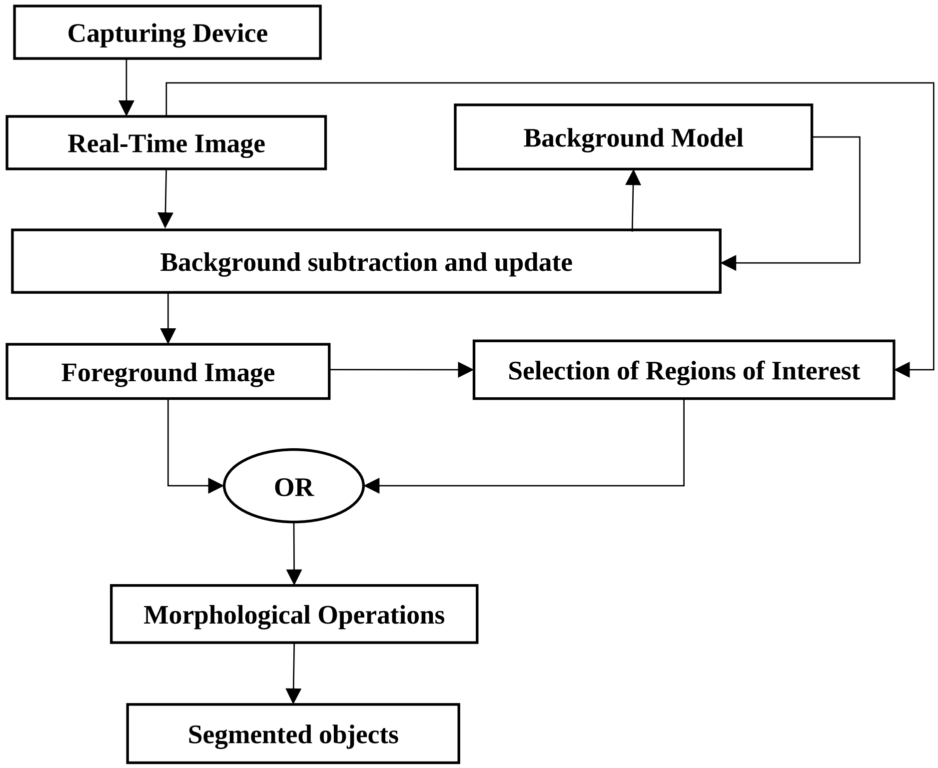

Fig. 1 Block diagram of the motion segmentation process

- $Mean_k$: represents the average of the grey levels of the frame's pixels at instant k of the video;
- Δ_k: it is the modulus of the average variation of the gray levels of the video pixels in the interval $[k - p\ , k]$ defined by equation (8).

$$\Delta_k = Mean_k - Mean_{k-p}, \quad k > p \tag{8}$$

The use of equation (8) in calculating the dynamic threshold allows the adjustment of the result as a function of the detected variations. When there is an increase in the variation of gray levels according to equation (7), the Th_k threshold value also increases, and when there is a decrease in the gray level variation, the Th_k Value also decreases, considering p sufficiently small.

3.2.5 Dynamic Learning Rate Calculations

Applying the dynamic threshold allows the improvement of the quality of the segmentation and helps the system adapt dynamically to the variations of the environment. Based on this idea and the desire for greater robustness, [43] states that for each frame k of the video sequence, in addition to the dynamic binarization threshold, the learning rate α_k Utilised in equation (3) that controls the background update speed.

Based on the vector of the history of variation of the gray levels of the pixels of the image, α_kThe learning rate can be estimated by equation (9):

$$\alpha_k = a + b\frac{|\alpha_k|}{\max(Mean_k, Mean_{k-p})}, \quad k > p \tag{9}$$

Where:

- α_k: represents the learning rate calculated at instant k;
- a: is the smallest value that α_k assumes, in proposed application a = 0.05;
- b: value parameterized by the user that characterizes the slope of the learning rate, which in the proposed application has a value of 0.85 obtained empirically;
- p: indicates the size of the stored scene lighting variation history, which in the proposed implementation is equal to 4.

Equation (9) is the analytical expression of a line that passes through a point of origin a, and has a slope b. The input variable of the equation is a normalized value calculated for each instant k. It is directly proportional to the variation of the gray level intensity in the $p + 1$ frames used to store the mundane lighting history in the scene. The equation outputs the learning rate for that instant k.

As a practical aspect, applying equation (9) with optimal input parameters promotes an improvement in the behavior of the background update process. Thus, the system's learning speed is subject to a dynamic adjustment characterized by acceleration or deceleration of the process as a function of the temporal variation of the average intensity of the gray levels of each image.

4. Results and Discussion

4.1. FPGA Implementation

The removal of the background allows moving and halted objects to be recognized. The stopped objects can be observed for a given amount of time before blending into the background, depending on the background model update mechanism [44]. The disadvantage of this method is that it detects where the previously stationary object, which was part of the background, began to move. The phrase "ghost" refers to a background object that has been shifted. The space where the object was before it began moving attracts attention until it fades into the background. Simple solutions use a non-selective background update, which means that data from every pixel of the current image is incorporated into the background model regardless of the segmentation outcome. As a result, pixels from moving objects are mixed in with the background, lowering the segmentation's selectivity. The background model, updated selectively, can only include pixels that are not detected as moving objects.

4.2. Block for Detecting Temporal and Spatial Edges

A pure background subtraction pixel misses many temporal and spatial (TP) edges, especially in low-light situations. In the worst-case scenario, a large portion of the moving vehicle may go undetected. Except for the automobile lights, it was completely dark at night. To overcome such a challenge, as a result of this issue, a new detection system has been developed; edge detection was used to introduce it. By detecting the edges by increasing the number of segments, the segmentation quality improves the total number of TP pixels. There are two edge-detecting blocks. Edge detection on both a temporal and geographical scale has been used blocks. The detection of temporal edges is done via the temporal edge detection block.

The Sobel operator is frequently employed in image edge detection. Compared to basic gradient operators, it has the advantage of being able to correct noise sensitivity. It is based on the estimation of an image intensity gradient function. It uses two spatial masks (Hx and Hy), composed of 33 pixels and convolved with the source image, to create gradient approximations. Because the Sobel operator only utilises two masks to identify edges in horizontal and vertical dimensions, its edge detection accuracy is limited. The Sobel compass operator, which uses a higher number of masks with closely spaced orientations, can overcome this problem. Methods use a non-selective background update, which means that data from the background is updated regardless of the segmentation result. The four masks, H0, H45, H90, and H135, must be applied to each input pixel.

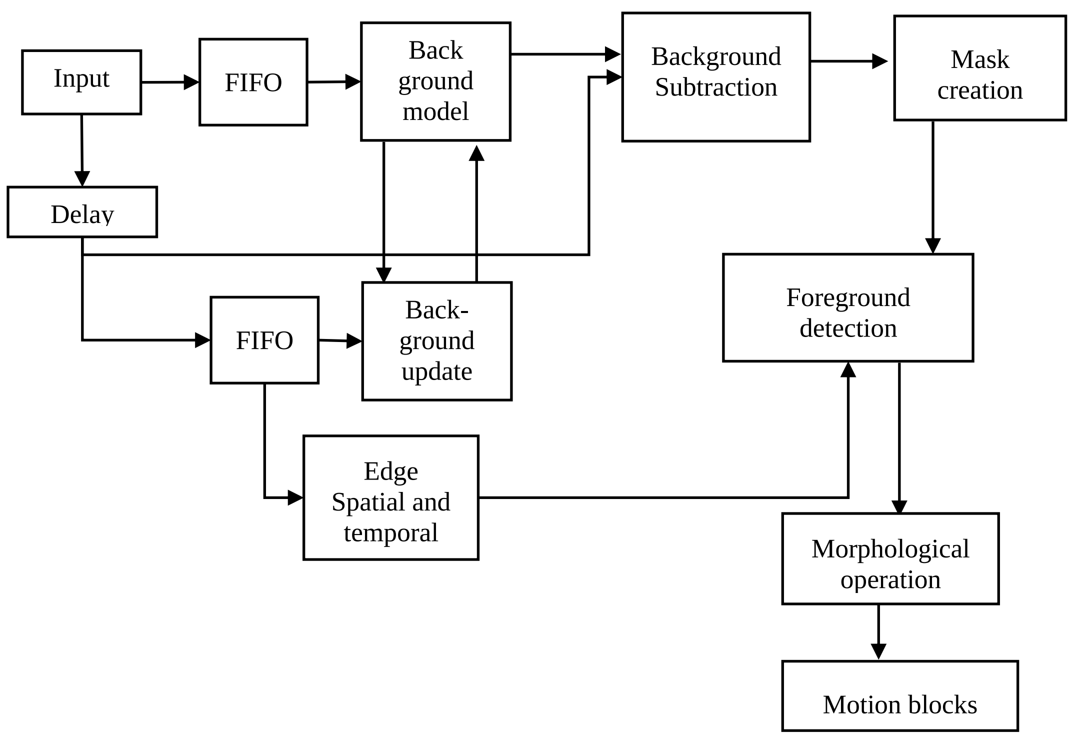

Fig. 2 Block diagram for FPGA implementation of proposed moving object detection

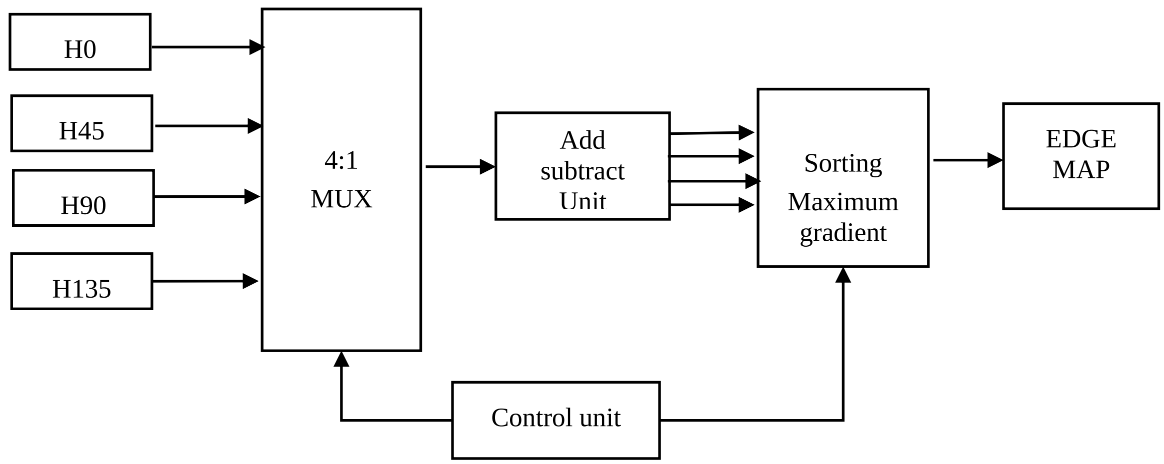

Fig. 3 Edge detection block

The advantage of the Sobel compass edge detector is that it does not require the computation of squares or square roots, which are considered somewhat expensive operations.

It proceeds through MUX, and selecting the relevant mask is controlled by a controller in different time shifts according to the memory buffer. The selected mask is processed by the processing unit, where gradients are calculated, and the gradient maximum is selected for edge map processing.

4.3. Simulation Results

This paper examines four background subtraction approaches for image segmentation at the scene using the CDNet dataset [45]. The database contains 1700 frames with a resolution of 320×240; the first 100 frames are used for background initialization, and the remaining photos are utilised for object detection background updates. The simulation result for the input frame is shown in the diagram below.

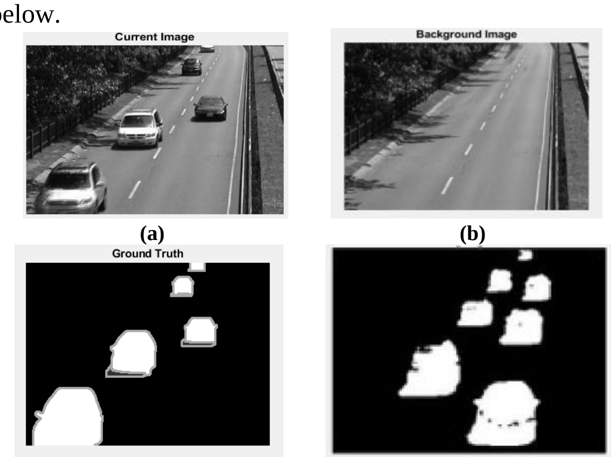

Fig. 4 (a) Input frame (d) Background image (c) Ground truth (d) Segmented Result

Table 1. Comparison of the proposed algorithm's selected design parameters to the implementation described in [46]

Parameter	**Implementation of [46]**	**Implementation of Proposed Approach**
Image resolution (pixels)	640×480	320×240
FFs used	1316 (4.3%)	782 (2.7%)
LUTs used	1232 (4.0%)	1772 (5.5%)
Block RAMs (Mbits)	0.34 (9.9%)	(47.9%)

The decreased sensitivity came at the expense of saving a significant amount of electricity and FPGA resources. The algorithmic results nevertheless seem to be enough for this application. The segmentation technique used in the implementation described in [47] is based on the MOG method and employs monochrome images of VGA resolution, which should work better for nonstationary backgrounds. The system described in this study is designed to function with images of lesser resolution. Still, it also includes a geometrical image modification block and edge and shadow detection blocks, which should improve detection sensitivity. The comparison in Table 2 also includes the area-optimized variation of the decreased functionality to demonstrate the potential speed of the proposed algorithm.

Table 2. Device Utilization summary

Count of Slices	363 out of 768 (20%)
Slice Flip-Flops Count	119 out of 1536 (7%)
LUTs with four inputs	469 out of 1536 (17%)
Logic-based on numbers	1158
The number of RAMs used	92
Total number of IOs	108
The total number of bonded IOBs	79 out of 124 (63%)
Flip Flops by IOB	32
GCLKs in number	3 out of 8 (37%)

5. Conclusion

This research presents an integrated technique for extracting moving objects from a real-time video feed. The processing steps were carefully selected and designed to ensure a straightforward implementation in specialized hardware like FPGA or ASIC. A few novel ideas are also developed to improve the algorithm's robustness while making it simple to implement on hardware. The detection quality is increased by using a new combination of masks from selective and non-selected backgrounds. In various lighting circumstances, the non-linear brightness adjustments enable precise shadow and highlight identification. To make the hardware simpler, morphological procedures are used. The proposed method was implemented in FPGA and tested in a real-world environment. The results of the tests showed that the proposed method for detecting moving objects is practical. Automatic day and night recognition and switching between highlight and shadow detection may be added in the future.

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