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Fpga Based Moving Object Detection Algorithm Implementation for Traffic Surveillance

Mayur Salve, Mahesh Rajput, Sanket Shingate
(Department of Electronics, Mumbai University, India

ABSTRACT
The main objective of this paper is detection of vehicles by background subtraction technique and the automatic surveillance of traffic based on the number of vehicles. The algorithm takes into consideration three main techniques namely Background Subtraction, Edge Detection and Shadow Detection. Background Subtraction block is sub-divided into Selective and Non-selective parts to improve the sensitivity and give accurate background. Edge detection helps to detect the exact boundaries of moving vehicles. This is followed by the shadow detection block that removes the falsely detected pixels that are generated due to shadow of the vehicle. By analyzing the output of the blocks discussed above, the final mask is generated. The mask along with the input frame is processed to give the final output frame where the detected object is highlighted. Furthermore, parameters such as number of blobs per frame (vehicles) and the area of blobs can be used for traffic surveillance. The algorithm of object detection is implemented on FPGA using VHDL. Spartan-6 Development Board is used for implementation of the same.
Keywords – FPGA, Image Processing, SPARTAN6, Traffic surveillance, VHDL.

I. INTRODUCTION

Various type of traffic surveillance systems are often used for controlling traffic and detecting unusual situations, such as traffic congestion or accidents. This paper describes an approach which detects moving and recently stopped vehicles using the novel technique of background subtraction [1] [2]. The algorithm is programmed, simulated and tested in VHDL and then implemented on the FPGA SPARTAN6 Board. The result of the algorithm is a binary mask image of blobs representing the detected objects. The background is updated slowly with Selective and Non-selective algorithm. The use of two updating blocks improves the sensitivity of the algorithm. Also shadow detection block maintains consistency of the algorithm by eliminating the error introduced by shadow of an object.

1.1. About FPGA

Field Programmable Gate Arrays (FPGAs) represent reconfigurable computing technology, which is in some ways ideally suited for video processing. Reconfigurable computers are processors which can be programmed with a design, and then reprogrammed (or reconfigured) with virtually limitless designs as the designers need change. All of the logic in an FPGA can be rewired, or reconfigured, with a different design as often as the designer likes. This type of architecture allows a large variety of logic designs dependent on the processors resources), which can be interchanged for a new design as soon as the device can be reprogrammed. Engineers use a hardware language such as VHDL, which allows for a design methodology similar to software design. This software view of hardware design allows for a lower overall support cost and design abstraction.

1.2. About VHDL

VHDL is an acronym for Very High Speed Integrated Circuit Hardware Description Language. It is a hardware description language that can be used to model a digital system at many levels of abstraction, ranging from the algorithmic level to the gate level. The VHDL language has constructs that enable you to express the concurrent or sequential behaviour of a digital system. It also allows you to model the system as an interconnection of components. Test waveforms can also be generated using the same constructs.

1.3. Algorithm

Each pixel is modified independently using the statistical procedure of Gaussian distribution [3] and the pixels of the moving object is detected using the inequality mentioned below:

$$|I_t - \mu_t| < k \cdot \sigma_t \quad (1)$$

Where μ_t and σ_t are mean and standard deviation matrices of Gaussian distribution for image pixel intensities and constant k typically has a value between 2 and 3.The updating background image is calculated as shown by the following equations:

$$\mu_t(x,y) = \alpha \cdot I_{t-1}(x,y) + (1-\alpha) \cdot \mu_{t-1}(x,y) \quad (2)$$

$$\sigma_t^2(x,y) = \alpha[I_{t-1}(x,y) - \mu_{t-1}(x,y)]^2 + (1-\alpha) \cdot \sigma_{t-1}^2(x,y) \quad (3)$$

Where I_{t-1} and μ_{t-1} is the intensity of previous image frame and previous frame and $\boldsymbol{\alpha}$ is learning ratio.

II. NON-SELECTIVE BLOCK

The task of detecting the moving and recently stopped vehicles is done by the non-selective block. The equation for non-selective background updating [2] [4] is given by:

$$\mu_{N,t}(x,y) = \begin{cases} \mu_{N,t-1}(x,y) + \delta_{N1} \text{ if } I_t(x,y) > \mu_{N,t-1}(x,y) \\ \mu_{N,t-1}(x,y) - \delta_{N1} \text{ if } I_t(x,y) > \mu_{N,t-1}(x,y) \\ \mu_{N,t-1}(x,y) \text{ otherwise} \end{cases} \quad (4)$$

Where I_t *(x y)* is the brightness of a pixel situated at coordinates (x,y) of input monochrome image at the time t; $\mu_{N,t}$ *(x,y)* the brightness of a pixel situated at coordinates (x,y) of background image, updated non-selectively; δ_{N1} = 2-5 = 0.03125 is a small constant evaluated experimentally. It is assumed that the brightness of the input image is in the range: *It(x,y)* □ □<0,255>.

The updating of □□□τ which is □□ from (1) for non-selective model [2] is given by (5):

$$\sigma_{N,t}(x,y) = \begin{cases} \sigma_{N,t-1}(x,y) + \delta_{N1} \text{ if } |I_t - \mu_{N,t-1}| > \sigma_{N,t-1} \\ \sigma_{N,t-1}(x,y) - \delta_{N1} \text{ if } |I_t - \mu_{N,t-1}| < \sigma_{N,t-1} \\ \sigma_{N,t-1}(x,y) \text{ otherwise} \end{cases} \quad (5)$$

where □□□□ is experimentally evaluated to be 0.00390625 (i.e. 2^{-8}). The values of $\mu_{N,t}$ and □□□□ are used to calculate the pixel values of m_N from equation (1).

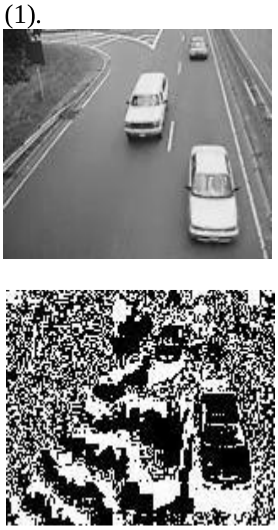

Figure 2: Showing I_t *(x,y)* and m_N *(x,y)* respectively.

III. Selective Block

This block is similar to the non-selective block, but it depends on the final mask output [4] as shown by (6):

$$\mu_{S,t}(x,y) = \begin{cases} \mu_{S,t-1}(x,y) + \delta_{S1} \text{ if } I_{t-1}(x,y) > \mu_{S,t-1}(x,y) \\ \quad \text{and } m_{VTS,t-1}(x,y=0) \\ \sigma_{S,t-1}(x,y) - \delta_{S1} \text{ if } I_{t-1}(x,y) > \mu_{S,t-1}(x,y) \\ \quad \text{and } m_{VTS,t-1}(x,y=0) \\ \sigma_{S,t-1}(x,y) \text{ otherwise} \end{cases} \quad (6)$$

$$\sigma_{S,t}(x,y) = \begin{cases} \sigma_{S,t-1}(x,y) + \delta_{S2} \text{ if } |I_{t-1}(x,y) - \mu_{S,t-1}(x,y)| \\ \quad > \sigma_{S,t-1}(x,y) \text{ and } m_{VTS,t-1}(x,y=0) \\ \sigma_{S,t-1}(x,y) - \delta_{S2} \text{ if } |I_{t-1}(x,y) - \mu_{S,t-1}(x,y)| \\ \quad < \sigma_{S,t-1}(x,y) \text{ and } m_{VTS,t-1}(x,y=0) \\ \sigma_{S,t-1}(x,y) \text{ otherwise} \end{cases} \quad (7)$$

where $m_{VTS,t}$ *(x, y)* = $m_{V,t}$ *(x, y)* ∨ $m_{ET,t}$ *(x, y)* □ $m_{ES,t}$ *(x, y) ;* □$_{S,t}$ *(x, y)* – the brightness of a pixel at coordinates (x, y) of background image updated using selectivity; m_V *(x, y)* – the element of the detected vehicle mask image of value equal to 0 or 1, where 1 denotes the detected moving objects. The values of constants □$_{S1}$ and □$_{S2}$ were established experimentally: □$_{S1}$ = 0.25, □$_{S2}$ = 0.03125 for I_t□□ *x, y)* □ □ □ 0,255>From (1), the image frame m_s comes out as shown below:

Figure 3: Showing m_s*(x,y)*

IV. Binary Mask Combination Block

The output from both selective and non-selective block is combined into a single binary mask. A simple AND operation is not enough to detect all the pixels. Hence a special combination of AND and OR operations [5] are used to improve the detection as shown (8):

$$m_B(x,y) = \begin{cases} m_S(x,y) \vee m_N(x,y) \text{ if } ((m_S(x-1,y) \wedge m_N(x-1,y)) \\ \quad \vee (m_S(x-1,y-1) \wedge m_N(x-1,y-1)) \\ \quad \vee (m_S(x,y-1) \wedge m_N(x,y-1)) \\ \quad \vee (m_S(x+1,y-1) \wedge m_N(x+1,y-1)) \\ m_S(x,y) \wedge m_N(x,y) \text{ otherwise} \end{cases} \quad (8)$$

Figure 4: Showing m_B*(x,y)*

V. Temporal and Spatial Edge Detection

During a dark scene, True Positive pixels [2] may not be detected and a major portion or the car may be neglected. So to improve the segmentation quality, the TP pixels need to be increased. This is done by using two type of edge detection: Temporal and Spatial Edge Detection blocks.

In temporal edge detection block, the edges are detected by taking the difference of the current and previous frame:

$$\Delta I_T = |I_t - I_{t-1}| \qquad (9)$$

In spatial edge detection, the difference of current image and background is taken as below:

$$\Delta I_S = |I_t - \mu_{N,t}| \qquad (10)$$

Temporal and spatial edge image mask m_{ET} and m_{ES} respectively is given by the following equation:

$$m_{ET}(x,y) = \begin{cases} 1 \text{ if } |\Delta I_T(\mathrm{x},\mathrm{y}) - \Delta I_T(\mathrm{x}-1,\mathrm{y})| > \theta_{ET} \vee \\ \quad |\Delta I_T(\mathrm{x},\mathrm{y}) - \Delta I_T(\mathrm{x},\mathrm{y}-1)| > \theta_{ET} \\ 0 \text{ otherwise} \end{cases} \qquad (11)$$

$$m_{ES}(x,y) = \begin{cases} 1 \text{ if } |\Delta I_S(\mathrm{x},\mathrm{y}) - \Delta I_S(\mathrm{x}-1,\mathrm{y})| > \theta_{ES} \vee \\ \quad |\Delta I_S(\mathrm{x},\mathrm{y}) - \Delta I_S(\mathrm{x},\mathrm{y}-1)| > \theta_{ES} \\ 0 \text{ otherwise} \end{cases} \qquad (12)$$

where θ_{ET} and θ_{ES} are constant threshold values.

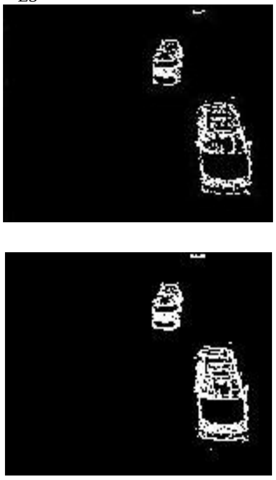

Figure 5: Showing m_{ET} and m_{ES} respectively.

VI. Shadow Detection

Shadows get detected and may be misunderstood by the system to be an object itself. Hence to remove any such discrepancies, the Shadow detection technique is used. By comparing the decrease in brightness [5] [6] [7], shadows are detected by the following equation:
where α and β are constant coefficients: α=0.55, β=0.95, both evaluated experimentally.

$$m_{SH}(x,y) = \begin{cases} 1 \text{ if } \alpha \le \dfrac{I_t(x,y)}{\mu_{N,t}(x,y)} \le \beta \\ 0 \text{ otherwise} \end{cases} \qquad (13)$$

Figure 6: Showing m_{SH}.

VII. Final Processing

The masks obtained by implementing the previous algorithms are combined into a single mask *M_Temp1*:

$$m_{HS} = dil(ero(\sim(m_{ET} \wedge m_{ES}) \wedge) m_{SH}) \qquad (14)$$

$$M_{Temp\ 1} = ero\Big(dil\big((m_B \wedge \sim m_{HS}) \vee (m_{ET} \wedge m_{ES})\big)\Big) \qquad (15)$$

where *dil()* and *ero()* denote 2x2 morphological dilation and erosion operation [2] respectively.
The mask thus obtained usually contains False negative and False positive pixels. Hence to improve the shape of the blobs, the inbuilt opening block is added to obtain the final frame of mask m_V.

Figure 7: Showing m_V.

VIII. CONCLUSION

In this paper, the combined algorithm for extracting moving objects from a stored video stream is proposed. The processing steps were carefully selected and adopted to provide simple and straightforward realization in specialized hardware, such as FPGA. A few novel ideas to enhance the algorithm are also developed, increasing the robustness and maintaining its simplicity for hardware implementation. The proposed method of background calculation, using running mode is very fast and requires only basic operations. The novel combination of masks from selective and non-selective background improves the detection quality. Shadow Detection in various light conditions improves the sensitivity. The application of Final Processing significantly improves the final blob mask. The test and simulation result proves the usability of the presented idea for recognizing the moving vehicles at low power consumption-the system properly found almost all of the moving vehicles during different climatic conditions.

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