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A NOVEL APPROACH FOR CHROMATIC SHADOW DETECTION AND TRACKING FOR TRAFFIC IMAGES USING PATCH- BASED BACKGROUND METHOD

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ABSTRACT:-

The need for detecting the fast moving objects has become necessary in various applications like video surveillance, motion detection etc. This paper proposes various methods for identifying the moving objects and then removes its shadows for clear perception of the moving object. Firstly, in this paper we perform background subtraction using Gaussian mixture background modeling to extract the moving object in the video stream. Later we perform the frame difference method on the same video and combine both the results to obtain the moving object we are interested in. Due to the effects of atmosphere, the moving objects in videos contain moving shadows. These shadows affect the performance of moving object detection. Shadows are eliminated by using the difference of texture feature and color information in gray foreground image and gray background image of the foreground object, and then detect the real foreground object.

Keywords-**Background Subtraction, Gaussian mixture background modeling, texture feature, color information. Shadow detection.**

1. INTRODUCTION:-

Discovery of moving targets is especially essential since individuals are normally interested by distinguishing or following such targets. Shadows exist as long as light sources are available for indoor or outside video checking. Finding the shadow can enhance the precision of moving target discovery. By observing continuously, an insightful video checking framework can gather huge data, for example, the number of guests, lines, and the number of vehicles etc. This kind of information leads to the establishment for the right observation of detecting targets. Existing methods for recognizing moving targets normally use the techniques in which the target is detected along with its shadow. Shadow location has been the subject of broad research in recent times. Shadow recognition techniques can

be characterized into two classifications: Spatial and Spectral based shadow detection methods.

The Spatial feature-based strategy recognizes the shadow by utilizing the geometrical and texture message on the objective, the situation, and the position of the light source. This method of shadow detection is based on the illumination and shape of the object. The spatial based methods work directly in the input frame but this method fails when the shadow has the same orientation as that of the object. Thenecessity for an earlier geometrical message is also a limitation for spatial shadow detection methods. In contrast to the spatial feature-based method, the spectral based technique is handier and well known since the message on the spectral range between the objective and shadowed area ordinarily depends on brightening and is about free of light source position and geometric shape. Spectral based methods use the chromacity, intensity and physical properties of the object. This paper proposes a technique for distinguishing an objective utilizing dual background models. A novel calculation is created that distinguishes moving shadows utilizing the shading data (YUV space) and surface data.

2. BACKGROUND SUBTRACTION:-

The most widely used method fordetecting moving objectsin videos is the Background Subtraction method. The basic background subtraction algorithm performs a difference operation on the current frame and a reference frame (which is also called background model).The background subtraction method process flow is shown in fig.1. The above algorithm does not fit well to dynamic scenarios like thieves wandering, river surface ripples etc. The algorithm should dynamically adapt to complex scenarios in real time. To meet these challenges we use Gaussian mixture background model to effectively identify the moving object. This method also cannot identify the irregular movement of the background accurately.

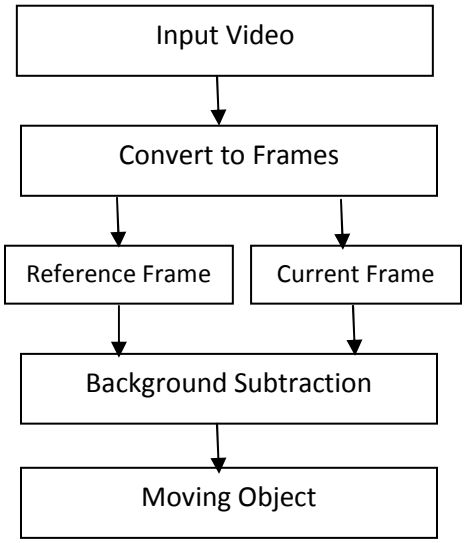


Fig.1:- Flowchart of Background Subtraction method

3. FRAME DIFFERENCE METHOD:-

Frame difference method is the simplest form of background subtraction. In this method the current frame, say f_i is subtracted from the previous frame, f_{i-1}. A proper threshold, let it be T, is selected to determine whether the pixel is in foreground or background. The difference between two pixels is calculated, and if the

difference value exceeds T, then the pixel is considered as foreground.

$$|f_i - f_{i-1}| > T$$

A binary image is formed after the frame difference since the pixel value greater than Threshold is represented as white and the remaining pixels are considered as black. This method is simple and computationally effective. It also eliminates the background noise. But in case of dynamic scenarios, the results of this method are not accurate. The flowchart of the frame difference method is shown in Fig.2.

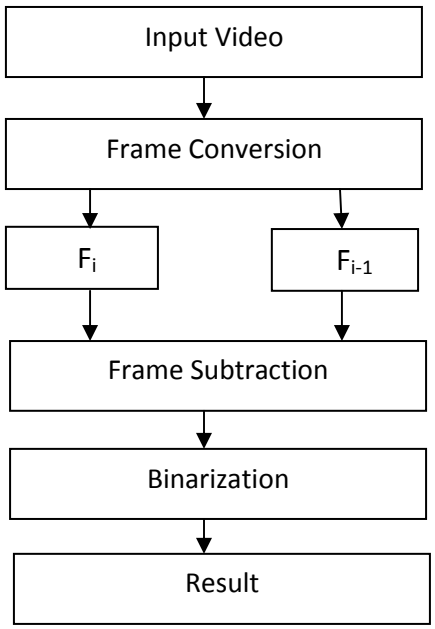


Figure 2: Flow Chart of Frame Difference Method

4. EXTRACTION OF FOREGROUNDUSINGDUALMODELING (PATCH-BASED BACKGROUND METHOS):-

To identify the moving objects in video sequences, either of the techniques (background subtraction or frame difference method) discussed earlier can be used. Si

nce the performance of these individual processes cannot give accurate results, in this paper we perform both the processes and integrate the results for better visualization of the moving object.

Considering that the frame difference method has low computational load and gives constant execution, the moving object area is first pre-extracted from the pre-prepared video. Be that as it may, the frame difference methodcannot fit well to complex dynamic situations, for example, vehicles moving, thieves wandering or waterway surface swells. Subsequently, the pre-removed moving object area contains some non-moving targets. Gaussian mixture background model is performed again on the pre-extracted moving object. Since the Gaussian mixture background model might be influenced by brightening, there are still a few shadows in the moving foreground removed along with these lines. The way toward extracting the moving object area utilizing dual models appears in Figure 3.

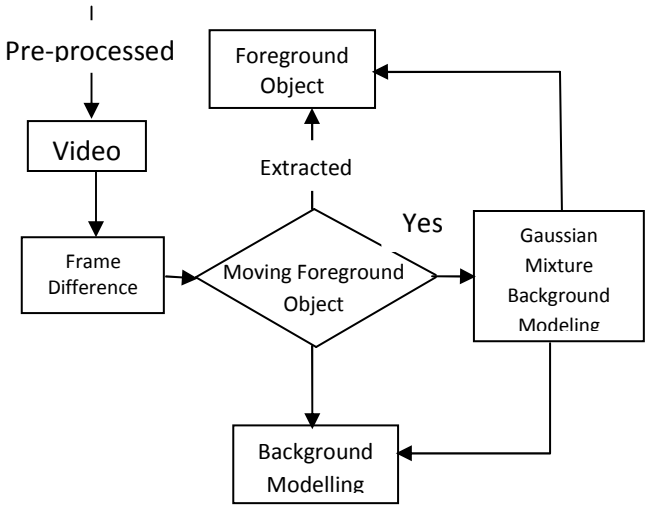


Figure 3: Foreground Extraction using dual models

5. SHADOW DETECTION:-

Numerous calculations have been proposed for shadow recognition, including the model-based strategy and the property-based technique. The model-based approach develops shadow models utilizing earlier information of situations, moving targets, and enlightenment. The built models are then used to precisely register shadow shape and area. By and large, earlier information isn't accessible; along these lines, the calculation is practical for particular applications.

The property-based strategy recognizes shadows by using their chromacity, shading, surface, inclination, intensity, and edge. These methods not only deal with geometric features but also deal with the spectral properties of shadows like color. These methods can be thresholding based or color information based. We can observe that the brightness of the shadow is much lesser when compared with the brightness of the surroundings, while Chrominance is relatively unaltered. Henceforth, shadow recognition in light of shading variety attributes is fundamentally accomplished by changing the space in which the original image is captured.

The goal is to recognize shadows by changing RGB pictures into HSV pictures, YUV pictures and, normalized RGB pictures. Surface data based shadow detection is exceptionally reliant on the distinction in brightness between pixels in the anticipated shadows and those in the surroundings. Brightness fluctuates significantly, while the surface is to a great extent unaltered. Thus, the LBP based surface calculation, for the most part, comes up short for areas with slight surface varieties, for example, the dark levels in the neighboring sky and grass pixels. In view of the qualities and shortcomings of the two calculations, this paper proposes a novel shadow recognition calculation. The process involves the transformation of image to YUV space and then performs LBP. A OR operation is performed on both and the result is obtained as depicted in Figure 4.

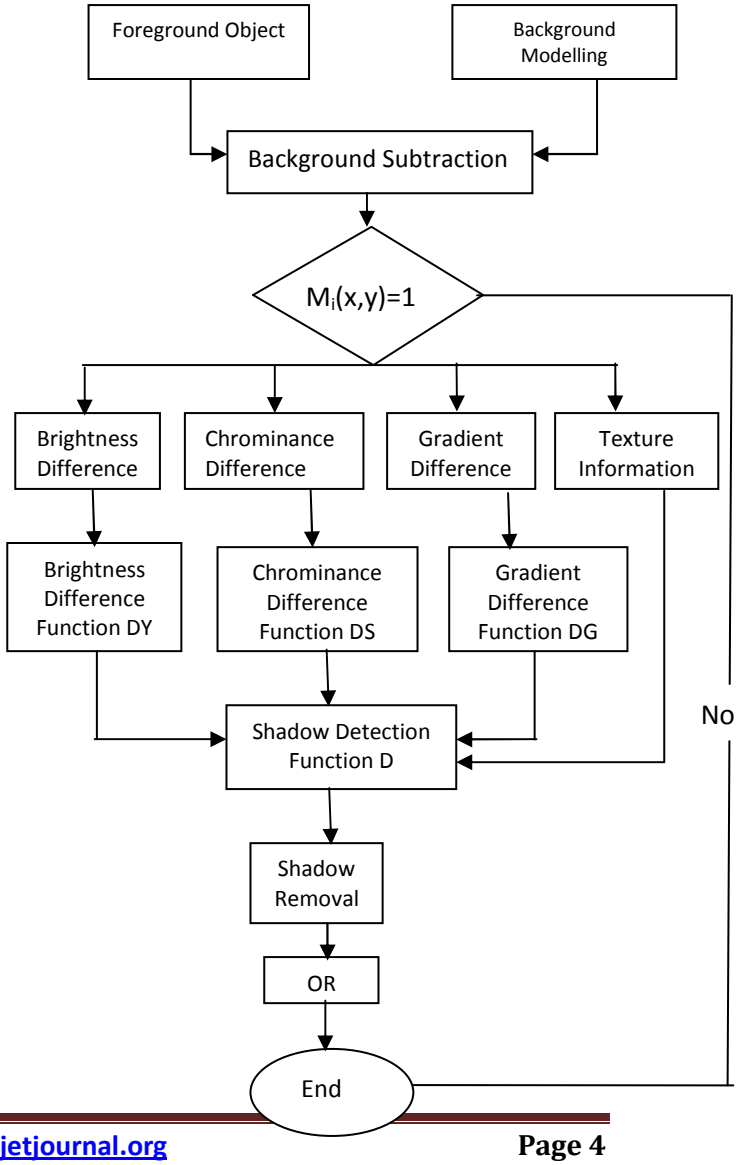


Figure 4: Shadow detection algorithm process

6. TRANSFORMATION TO YUV COLOR SPACE:-

It is very complex to analyze the images in RGB color space. We need to transform the RGB image to YUV color space to effectively analyze the moving objects in video sequences.

In the YUV color space, Y means to brightness and U and V signify the chrominance components R _Y and B_Y, individually. The quality of the YUV space is that brightness data Y and Chrominance data UV are commonly autonomous. Image data got from the video succession is more often than not in the RGB shading model. It can be changed over to YUV shading space by utilizing the accompanying conventional technique:

$$\begin{matrix} y \\ U \\ V \end{matrix} = \begin{matrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{matrix} \times \begin{matrix} r \\ g \\ b \end{matrix} \begin{matrix} 16 \\ +128 \\ 128 \end{matrix} \quad \ldots\ldots. (1)$$

Considering the ecological factor of brightening and camera ripple, the brightness and Chrominance of pixels in a few locales may change altogether. In this way, the RGB estimations of every pixel are supplanted with the mean of the 3×3 neighborhood fixated on this pixel:

$$r = \sum_{i=1}^{9} \frac{R}{9}, \; g = \sum_{i=1}^{9} \frac{G}{9}, \; b = \sum_{i=1}^{9} \frac{B}{9} \quad \ldots\ldots (2)$$

For estimating the RGB values of the current image and the background model, use the equation (2). To convert the RGB image to YUV color space, utilize the condition (1).

To detect the shadow of the moving objects, we define the difference functions of the image properties which mainly include brightness, Chrominance and Gradient. Gradient is the directional change (usually from low to high intensity values) in the intensity of color in an image. These functions perform the difference operationon the current picture and the background model.

Consider a pixel in the input image, say M_i (x, y) = 1 which determines the pixel for the position (x, y) in the ith input frame and the background frame, subtract the pixel brightness to acquire the brightness difference function. A threshold is selected to decide whether the pixel is in the shadow region. The brightness difference function is denoted as DB.

In the same way, the Chrominance difference (DC) and Gradient difference (DG) is calculated upon each pixel value to analyze whether the pixels are in projected shadow region or in the foreground region. At last we combine all these difference functions to extract a common function which decides the shadow in the moving object we are interested in.

The shadow function, D is given as-

$$D(x, y) = DB(x, y) \times DC(x, y) \times DG(x, y) \times \beta \quad \ldots\ldots.. (3)$$

Here, β is an additional factor which is used to improve the performance of the shadow function. The value of β ranges from 0 to 1.

7. LOCAL TEXTURE SHADOWS ELIMINATION USING LOCAL BINARY PATTERN:-

LBP texture is a popular approach for shadow detection due to its discriminative power. It is an effective neighborhood surface descriptor because of its remarkable dark level and revolution invariance and low computational load. The guideline depends on choosing a middle pixel point and performing difference operation with that of its neighbors inside a range R. The middle pixel is taken as the threshold inside a range R. This parallel framework Speaks to dim level variety and its LBP esteem are processed. A high range implies more noteworthy precision in speaking to nearby dark level variety, however, requires a more computational load. Here (P, R) = (8, 1), the exactness and constant execution meet the general framework prerequisites. This paper enhances the first LBP administrator in an accompanying way:

$$u\,(g_i\text{-}g_0)=\begin{cases}1 & |gi-g0| \geq 10\\ 0 & |gi-g0| < 10\end{cases} \quad \ldots\ldots.. (4)$$

$$LBP_{P,R}(x_0,y_0)=\sum_{i=0}^{P-1} S(g_i\text{-}g_0)2^i \quad \ldots\ldots.. (5)$$

Whenever $M_i(x, y) = 1$ for the position (x, y) in the i input picture and in the ibackground picture, subtract the LBP estimation of these two positions utilizing Condition (4) and Condition (5). Think about their total esteems and characterize limits to decide if the closer view pixel is in the anticipated shadow.

8. OR OPERATION:-

The picture standardization based strategy for dispensing with shadows utilizing the YUV shading space is subject to limitations and is inclined to identify a moving focus on whose brightness is like the background yet higher than the shadow, accordingly disposing of it as the shadow. In any case, the LBP in view of nearby surface disposal calculation can keep up brilliant districts where the forefront target is found. The purpose behind this is the splendid area fluctuates more than dull locales of the forefront target and its surface is more obvious. Subsequently, these two techniques supplement each other. The OR operation-based shadow district can be spoken to as:

$$Sh=\begin{cases}0 & Shcolor(x,y)=0\ andShLBP(x,y)=0\\ 1 & others\end{cases}$$

9. EXPERIMENTAL RESULTS:-

To achieve the expected results on the proposed techniques, tests were conducted on the video of a vehicle in traffic. We can observe the video subjected to different methods and its corresponding results in the below Figures.

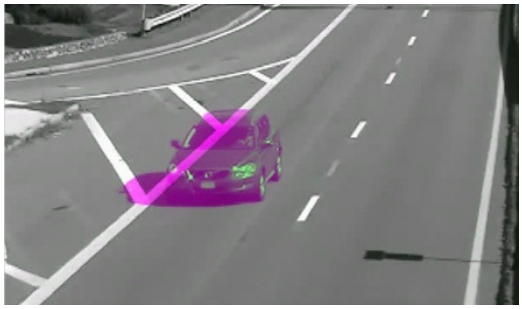
The original image obtained from video sequence and its corresponding background model is shown in Figure (a) and Figure (b). The foreground target is shown in Figure (c). The white area in the output images denote $M_i(x, y) = 1$ and the black areas have the pixel value $M_i(x, y) = 0$ for frame i in both the foreground and background image.

The Brightness, Chrominance and Gradient difference functions of the image in calculated in YUV color space is shown in Figures (d), (e), (f).

With the correction factor β not included, the moving object identification is shown in Figure (g). The same calculations are done adding the correction factor β shown in Figure (h) which clearly shows the improvement in the image. The image obtained after the LBP operation is shown in Figure (i) and the final foreground target is shown in Figure (j).

a. Originalimage

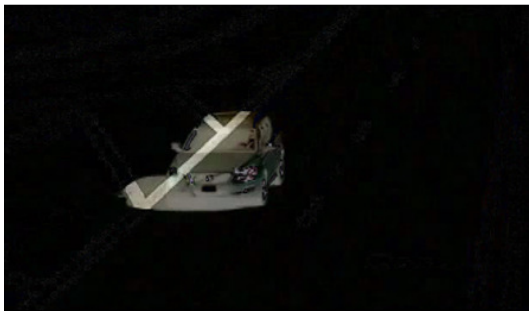
b.Background model



c. Foreground target

d. Image after performing Brightness difference function

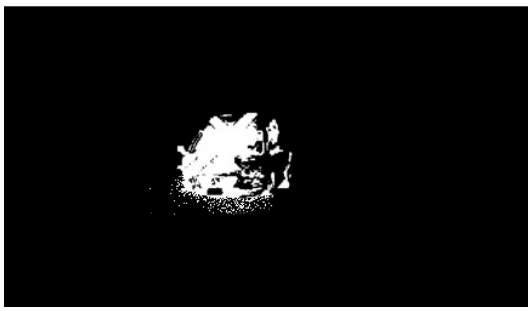
e. Result after Chrominance difference



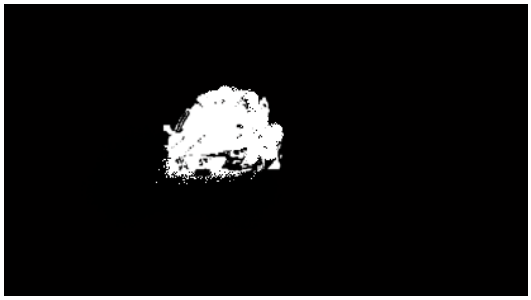
f. Gradient density difference

g. Shadow eliminationbefore addingβ

h. Shadow elimination after the addition of β



i. Local texture image



j. Final foreground target

10. CONCLUSION:-

The paper proposes the methods that improve the detection of moving objects. Various novel algorithms are proposed which detect the moving objects using dual background models. A technique of recognizing and eliminating the shadows based on their color space (YUV) and texture information was also discussed. Additional correction factor ß was also added to improve the performance of shadow detection function. The proposed techniques are flexible and have low computational load and its efficiency was also confirmed.

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