

# Motion Based Approaches For Object Detection

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# Introduction

- ❑ Motion based approaches for object detection involve various techniques to detect any object under motion.
- ❑ These are used in computer vision with the help of image processing.
- ❑ Multiple consecutive frames from a video are compared by various methods to determine if any object is moving.

# Introduction

- ❏ Motion of images is actually a sequence of static frames that is induced by the brain as actual motion and the techniques to compute this motion can be classified as-
  - Feature-based Methods
  - Direct, Dense Methods

# Introduction

- **Feature-based Methods-**
  - Extract visual features (corners, textured areas) and track them over multiple frames.
  - Sparse motion fields, but more robust tracking.
  - Suitable for larger pixel size and dynamic changes in frames.

# Introduction

- **Direct, Dense Methods-**
  - Directly recover image motion at each pixel from spatio-temporal image brightness variations.
  - Dense motion fields, but sensitive to appearance variations.

# Techniques For Moving Object Detection :-

- Background Subtraction
  - Frame Differencing
  - Mean Filtering
  - Median Filtering
- Optical Flow

# Background Subtraction :-

- ❑ Background subtraction is any technique which allows an image's foreground to be extracted for further processing (object recognition etc.).
- ❑ The rationale in the approach is that of detecting the moving objects from the difference between the current frame and a reference frame, often called "background image", or "background model".

# Background Subtraction :-

Steps to do background subtraction:-

- A. Estimate background for time  $t$ .
- B. Subtract estimated background from current input frame.
- C. Apply a threshold to the absolute difference to get the foreground mask.



# Background Subtraction<sup>[1]</sup> :-

Image at time  $t$ :  
 $I(x, y, t)$



Background at time  $t$ :  
 $B(x, y, t)$



$| > Th$

# Background Subtraction :-

- ❑ Now a question will arise i.e, What is a good estimate for the background?
- ❑ So,let us see some of the approaches.

## ➤ Frame Differencing : -

→ Background is estimated to be the previous frame:

- $\mathbf{B(x,y,t) = I(x,y,t-1)}$

→ Background subtraction then becomes:

- $|\mathbf{I(x,y,t)-I(x,y,t-1)}| > \mathbf{Th}$

## ➤ Frame Differencing<sup>[1]</sup> : -

Image at time  $t$ :

$$I(x, y, t)$$



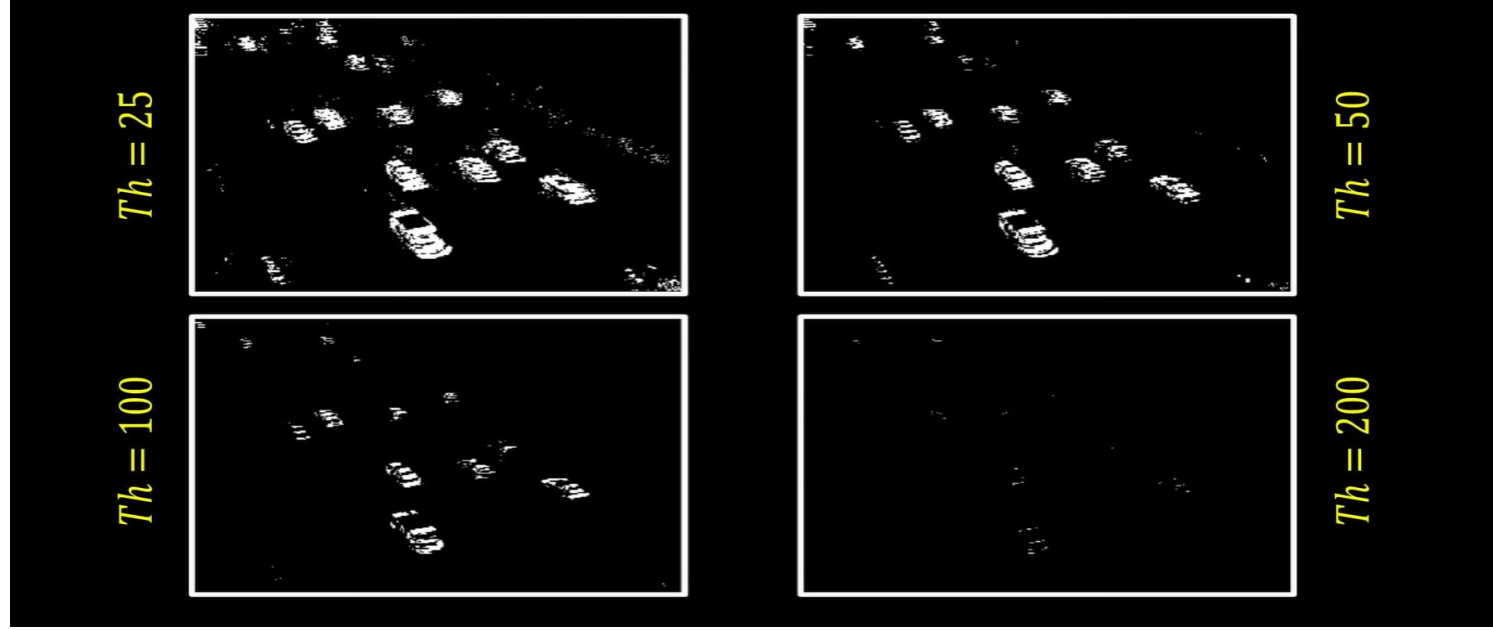
Background at time  $t$ :

$$B(x, y, t) = I(x, y, t - 1)$$



$$| > Th$$

## ➤ Frame Differencing<sup>[1]</sup> : -



## ➤ Frame Differencing : -

Limitations in this approach -

- ❑ Speed of the object
- ❑ Global Threshold
- ❑ Object Structure
- ❑ Frame Rate

## ➤ Mean Filtering<sup>[2]</sup> :-

- In this case, background is the mean of the previous  $n$  frames:

$$B(x, y, t) = \frac{1}{n} \sum_{i=1}^n I(x, y, t - i)$$

- Therefore, foreground mask is computed as:

$$\left| I(x, y, t) - \frac{1}{n} \sum_{i=1}^n I(x, y, t - i) \right| > Th$$

## ➤ Mean Filtering<sup>[2]</sup> :-



Estimated background



Foreground mask

Time window:  $n = 10$

→  $n$  is sensitive to random noise



## ➤ Median Filtering<sup>[3]</sup> :-

- Assuming that the background is more likely to appear in a scene, we can use the median of previous  $n$  frames as the background model:

$$B(x, y, t) = \text{median}\{I(x, y, t - i)\}$$

- Therefore the foreground mask is computed as:

$$|I(x, y, t) - \text{median}\{I(x, y, t - i)\}| > Th$$

where  $i \in \{1, \dots, n\}$

## ➤ Median Filtering<sup>[3]</sup> :-



Estimated background



Foreground mask

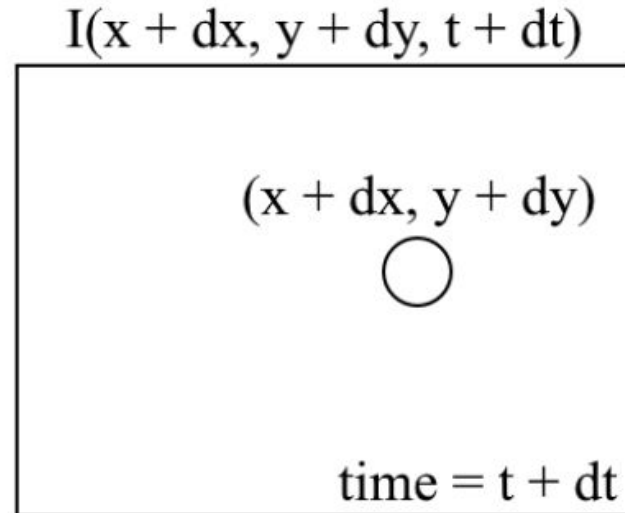
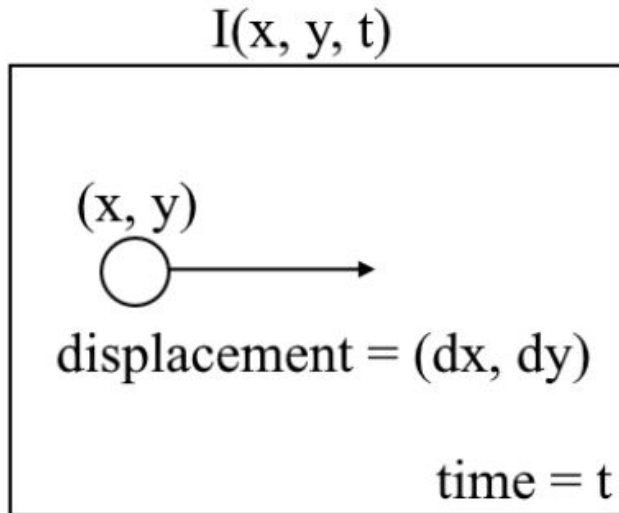
Time window:  $n = 10$

- $n$  is less sensitive to noise as compared to mean filter.
- Small value of  $n$  causes problem

# Optical Flow

- ❑ **Optical flow** is the motion of objects between consecutive frames of sequence, caused by the relative movement between the object and camera.
- ❑ The cardinal surroundings are in a three-dimensional coordinate system with time as an extra variable. As in image it is converted into a two-dimensional coordinate system with time as the third variable.
- ❑ Optical flow is expressed by the figure in next slide.

# Optical Flow<sup>[5]</sup>



# Optical Flow<sup>[5]</sup>

- ❑ Between consecutive frames, we can express the image intensity ( $I$ ) as function of space  $(x,y)$  *and time* ( $t$ ). In other words if we take the first image  $I(x,y,t)$  and move its pixel by  $(dx,dy)$  over time  $t$  we obtain the new image  $I(x+dx,y+dy,t+dt)$ .
- ❑ First we assume that the pixel intensities of the object are constant between the consecutive frames.

$$I(x, y, t) = I(x + \delta x, y + \delta y, t + \delta t)$$

# Optical Flow<sup>[5]</sup>

- By Taylor Series Approximation and removing common terms we get,

$$I(x + \delta x, y + \delta y, t + \delta t) = I(x, y, t) + \frac{\partial I}{\partial x} \delta x + \frac{\partial I}{\partial y} \delta y + \frac{\partial I}{\partial t} \delta t + \dots$$

$$\Rightarrow \frac{\partial I}{\partial x} \delta x + \frac{\partial I}{\partial y} \delta y + \frac{\partial I}{\partial t} \delta t = 0$$

# Optical Flow<sup>[5]</sup>

- Third we divide by  $dt$  to derive the optical flow equation,

$$\frac{\partial I}{\partial x} u + \frac{\partial I}{\partial y} v + \frac{\partial I}{\partial t} = 0$$

where  $u = dx/dt$  and  $v = dy/dt$

# Optical Flow

- ❑ This is the equation with two variables and cannot be solved. This is called *aperture problem*.
- ❑ To find optical flow another set of equations are needed given by additional constraints.
- ❑ One of the method to determine optical flow is Lucas Kanade method.



# Lucas Kanade Method for Optical Flow

- ❑ Additional constraints are considered to get required linear equations to get value  $u$  and  $v$ .
- ❑ Smooth flow of pixels is considered as one of the constraint i.e neighbourhood pixels also has same value of  $u$  and  $v$ .

$$\begin{bmatrix} I_x(\mathbf{p}_1) & I_y(\mathbf{p}_1) \\ I_x(\mathbf{p}_2) & I_y(\mathbf{p}_2) \\ \vdots & \vdots \\ I_x(\mathbf{p}_{25}) & I_y(\mathbf{p}_{25}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{p}_1) \\ I_t(\mathbf{p}_2) \\ \vdots \\ I_t(\mathbf{p}_{25}) \end{bmatrix}$$

# Lucas Kanade Method for Optical Flow

- ❑ All the linear equations are now solved to get the values of  $u$  and  $v$ .
- ❑ On the basis of this value of  $u$  and  $v$  flow is determined.

# Challenges :-

- ❑ **Illumination Variations**- Illumination variations result in major recognition errors, especially for appearance based techniques.
- ❑ **Camouflage**- The mixing of foreground (Object) and the background due to similarity of the texture.

# Challenges :-

- ❑ **Dynamic Scene Variations**- Object Detection techniques need to be incredibly fast at prediction time to meet the real-time demands of video process.
- ❑ **Aspect Ratio and Spatial Scale**- An object may appear in a wide range of sizes and aspect ratios in different scenes making the detection difficult.

# Applications<sup>[4]</sup> :-

- ❑ Video Surveillance.
- ❑ Human Activity Analysis.
- ❑ Road Condition Monitoring.
- ❑ Airport Safety.
- ❑ Monitoring Of Protection Along Marine Border.

## References :-

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THANK YOU