Background Modelling and Subtraction on Daubechies Wavelet Decomposition Using Object Detection

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Abstract: The project presents moving object detection based on background subtraction under Daubechies wavelet transform domain for video surveillance system. The object detection in the frequency domain will be approached to segment objects from foreground with an absence of background noise. Initially, it starts with background initialization by choosing start frame or taking initial few frames with the approximate median method. Then, DWT is applied to both current and initialized background frame generates sub-bands of low and high frequencies. Frame differencing will be done in this sub-bands followed by edge map creation and image reconstruction. In order to remove some unwanted pixels, morphological erosion and dilation operation is performed for object edge smoothness. The proposed approach has some advantages of background noise insensitiveness and invariant to varying illumination or lighting conditions. It also involves background updating model based on the current frame and previous background frame pixels comparisons. After the object detection, the performance of method will be measured (between frame ground truth and obtained result) through metrics such as sensitivity, accuracy, correlation and peak signal to noise ratio. This object detection also helps to track the detected object using connected component analysis. The use of proposed methodologies for effective object detection have better accuracy and with less processing time consumption rather than existing methods.

IndexTerms - video surveillance, DWT, morphological erosion, dilation, Frame differencing.

I. INTRODUCTION

With the rapid development of technologies, the object detection technology is used in the battlefield, volcanic forest, and community monitoring. As it can give abundant information such as image, video, and temperature, and have stronger information processing capabilities, such as image processing, target detection and location tracking and other advanced features. In the MSNs object detection and tracking technology based on video and images has been widely used. The technology of object tracking and detection was applied to video surveillance system to prevent security affairs .Recently, several object detection algorithms have been proposed. Generally, they can be classified into three methodologies; the background subtraction based, the frame difference based, and the optical flow method, to detect the moving objects in the cluttering background. Background subtraction is an approach for identifying the moving objects in a video sequence. It is the significant step in human-computer interaction, traffic monitoring, and video surveillance. The objective of frame differencing is to break a video into the background and the moving foreground objects. Each separate frame from the flow is compared against a reference frame. Once the reference is computed (often called a background model), then it will be updated with each newly arriving frame by exploiting frame differencing algorithm.Current frame pixels with considerable deviation from the background model is accounted to be moving objects. Background subtraction based on effective moving object detection using, Daubechies wavelet transform, frame differencing, morphological filtering and approximate median based background update. In general, the Daubechies wavelets are chosen to have the highest number A of vanishing moments, (this does not imply the best smoothness) for given support width 2A - 1. The two naming schemes which are in use, DN which uses the length or number of taps, and dbA refers to the number of vanishing moments. So, the wavelet transform D4 and db2 are same. For the moment and orthogonality conditions, there are 2A-1 possible solutions of algebraic equations, from which the chosen one has the external phase of scaling filter. The fast wavelet transform helps in practicing of the wavelet transform. The broad ranges of problems are widely solved using Daubechies wavelet, e.g. self-similar properties of a signal or fractal problems, signal discontinuities. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image, such as boundaries, skeletons, etc. We probe an image with a small shape or template called a structuring element in any given technique, which defines the interested region or neighborhood around a pixel. The algorithm is fast in speed and can solve the problem of the partially occluded target, which satisfies the requirements.

II. LITERATURE SURVEY

In the paper there were many methodologies followed like Threshold based segmentation, Gaussian mixture model, colour histogram gradient based algorithm , block-based background modelling . The depth study on object detection and tracking algorithm in multimedia sensor networks, the paper proposed a background difference method for camera networks to track objects in real time, which effectively solves the problem of limited resource on embedded platform and background change detection using wavelet transform.

A. ***Threshold based Segmentation*** is a segmentation based on a threshold difference between the present image and sequence of images by assuming that no successive changes occur in the background frames. The method of threshold-based segmentation is easy and fast in many applications, but while tracking multiple objects or when an object stops some problems appear. Hence, the other method is adopted; e.g. background subtraction, at the expense of updating the background. The difference in the image is classified to non-motion and motion based on a predefined threshold value. However, the suitable definition of the threshold value is the main problem with this method. Temporal difference is another method for motion detection and object detection .By using a temporal difference algorithm, Lipton extracts all moving objects. He adopts many variants on the DT method by applying temporal differencing (DT). To determine the absolute difference, the simplest one is to take consecutive video frames. Hence the changes are determined using the threshold function.

If the nth frame has the intensity In , then the pixel-wise difference function Δn is

$$\Delta n = |In - In{-}1| \quad (1)$$

and a motion image Mn can be extracted by thresholding **:**

$$M_n(\mu, v) = \begin{cases} I_n(\mu, v), & \Delta_n(\mu, v) \geq T, \\ 0 & \Delta_n(\mu, v) < T. \end{cases}$$

B. ***Gaussian Mixture Model*** is a an efficient adaptive algorithm using Gaussian mixture probability density for background subtraction. The parameters are constantly updated using Recursive equations and but also to simultaneously select the appropriate number of components for each pixel. In an on-line procedure, the algorithm can automatically fully adapt to the scene by choosing the number of components for each pixels . At time t we choose a reasonable time period T and we have X_T = { $x^{(t)}$, ..., $x^{(t-T)}$}. we update the training data set X_T and reestimate $\hat{p}(\vec{x}|X_T$, BG) for each new sample. However, from the recent history there could be some values that belong to the foreground objects and we should denote this estimate p($\vec{x}^{(t)}|X_T$ BG+FG). We use GMM with M components:

$$\text{p}(\vec{x}^{(t)}|X_T \ \text{BG+FG}) = \sum_{m=1}^{M} \hat{\pi}_m \, N(\vec{x}: \widehat{\overrightarrow{\mu_m}}, \widehat{\sigma_m}^2 I)$$

where $\widehat{\overrightarrow{\mu_1}}$, ..., $\widehat{\overrightarrow{\mu_M}}$ are the means estimate and $\widehat{\sigma}_1$, ..., $\widehat{\sigma_M}$ are the variance estimate that describe the Gaussian components. The covariance matrices are assumed to be identity matrix and diagonal matrix I has proper dimensions. The mixing weights denoted by $\widehat{\pi}_m$ are non-negative and add up to one. Given a new data sample $\vec{x}^{(t)}$ at time t the recursive update equations are:

$$\begin{aligned} \hat{\pi}_m &\leftarrow \hat{\pi}_m + \alpha(o_m^{(t)} - \hat{\pi}_m) \\ \hat{\vec{\mu}}_m &\leftarrow \hat{\vec{\mu}}_m + o_m^{(t)}(\alpha/\hat{\pi}_m)\vec{\delta}_m \\ \hat{\sigma}_m^2 &\leftarrow \hat{\sigma}_m^2 + o_m^{(t)}(\alpha/\hat{\pi}_m)(\vec{\delta}_m^T\vec{\delta}_m - \hat{\sigma}_m^2), \end{aligned}$$

where $\hat{\delta}_m = \vec{x}^{(t)} - \widehat{\overrightarrow{\mu_m}}$. Here constant α describes an exponentially decaying envelope that is used to limit the influence of the old data instead of the time interval T that was mentioned above. α = 1/T approximately we keep the same notation having in mind . For a new sample the ownership $o^{(t)}{}_m$ is set to 1 for the 'close' component with largest $\widehat{\pi}_m$ and the others are set to 0. If the Mahalanobis distance from the component is for example less than three standard deviations, we define that a sample is 'close' to a component. The squared distance from the m-th component is calculated as:

$$D^2{}_m(\vec{x}^{(t)} = \frac{\vec{\delta}^T{}_m \vec{\delta}_m}{\widehat{\sigma_m}^2})$$

A new component is generated with $\hat{\pi}_{M+1} = \alpha, \hat{\mu}_{M+1} = \vec{x}^{(t)}$ if there are no 'close' components and $\hat{\sigma}_{M+1} = \sigma_0$ where σ_0 is some appropriate initial variance. we discard the component with smallest $\widehat{\pi}_m$ if the maximum number of components is reached. Usually, the intruding foreground objects will be represented by some additional clusters which has small weights $\widehat{\pi}_m$. Therefore, the first B largest clusters we can approximate the background model:

$$\text{p}(\vec{x}^{(t)}|X_T \ \text{BG}) \sim \sum_{m=1}^{B} \hat{\pi}_m \, N(\vec{x}: \widehat{\overrightarrow{\mu_m}}, \widehat{\sigma_m}^2 I)$$

If the components are sorted to have descending weights $\widehat{\pi}_m$ we have:

$$\text{B} = \arg\min_b \left(\sum_{m=1}^{b} \hat{\pi}_m > \left(1 - c_f\right) \right)$$

where c_f is a measure of the maximum portion of the data that can belong to foreground objects.

C. ***Color Histogram and Gradient Based Segmentation*** *is* the method of initializing features of moving objects n by calculating the contours of the object to be tracked and recognizing the color features, the selected region's histogram of the color space is obtained as the feature of the description object by performing the difference operation on the two adjacent frames in the image sequence. Search the feature of the object. After the object feature is initialized, the particles can be spread around the object to search by using Uniform scattering or Gaussian scattering. the color characteristic of each particle is calculated according to the initial object feature and calculates the similar degree between the histogram vector of the object and the histogram vector of the spread particles. Then the normalization of similar particles and the sum of the similarities of all the particles is 1. The object state is observed through the diffusionresult. According to the similarity between particle and object , the weighted average is calculated. For example, the similarity between the image at the particle position 1 and the object are 0.3. The similarity between the image at the particle position 2 and the object is 0.04. The similarity between the image at the particle position 3 and the object is 0.011. The similarity between the image at the particle position k and the object is 0.005. The final weighted average was calculated. the particles are resampled . The resampling process of particles is based on the similarity to re-distribute thenumber of particles. The highest similarity will eject more particles nearby, while particles with low similaritiesare less likely to be scattered around them. The random sampling andre-sampling based on the importance is the main idea of the particle filter algorithm**.**

D. ***Block-Based Background Modelling*** is an effective approach for foreground detection. To generate background modelling both pixel-based and block-based processes are used to classify background pixels from those which belong to the foreground. The structure-texture decomposition is applied to the absolute difference image to minimize the noise in the results of the background subtraction. For segmentation, the structural component which contains the homogeneous parts of the image is used. Using a selected threshold the binary motion detection mask computation is made. The block-based and the statistical characteristics of a pixel is used by background model, in order to extract the static image (background image). The block-based background model generation includes the matrix representation and the calculation of probabilities. The background subtraction is used by computing the absolute difference between each frame of the video sequence and the developed background frame, after the background frame generation.For foreground detection, when the background image is generated from the background subtraction, the difference between the current image in the sequence and the background image is calculated. Then to decide if a pixel belongs to the background or to the moving object, a threshold operation is applied. The best threshold selection can be difficult. Most algorithm select threshold by testing a set of threshold values and then choose the one which gives the best results.

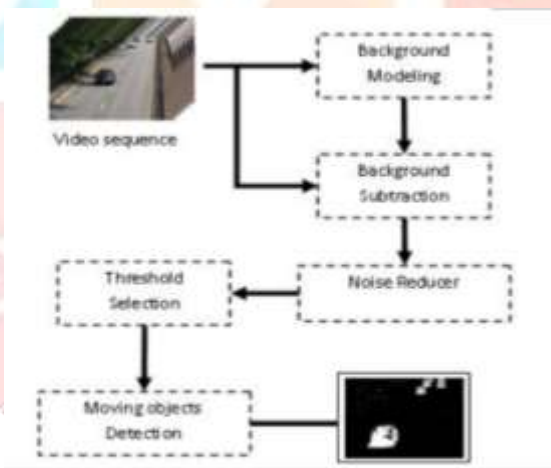


Fig.1.represents the moving objects detection processes used by our approach

E. ***Background Change Detection*** processes the system images in grayscale. Pre-processing involves the modeling of the predetermined background. The median function will be used to model the background. Subtraction process uses wavelets to process succeeding frames. Wavelets are actually grouped into families like Mexican Hat wavelets, Morlet wavelets, Daubechies wavelet and Haar wavelets. Most of these wavelets group have a number of characteristics in common. For object detection, Wavelet coefficients of the current frames will be obtained using the same family of the wavelet. A difference matrix stores the difference between the current frame coefficient and modeled background coefficients. The difference matrix will then be passed to the next block which is the object detection process. It will be responsible for obtaining the foreground from the result of subtraction process and then thresholding can be done . After applying this concept, if the element value of the difference matrix is greater than a specified threshold then it will be considered as part of the foreground as it denotes that there exists a change from the modeled background.

For object classification the basic AND operation functions by outputting a value of 1 only if all of its inputs are equivalent to 1. Applying this concept, given two consecutive foreground images containing only the moving and stationary objects both having a pixel value of 255 , a value of 255 will only be outputted if and only ifthe pixel value in the previous and current frame are bothequivalent to 255 .

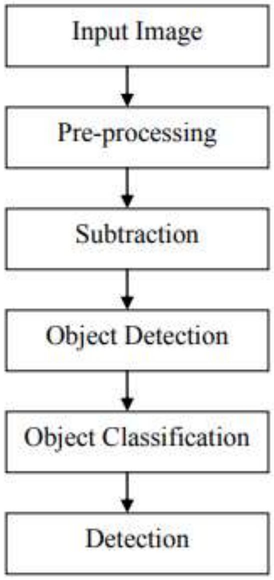


Fig 2. System Block Diagram

III. PROPOSED SYSTEM

With- in-depth study of background modeling and subtraction, the paper proposes the methodology of Daubechies wavelet decomposition using object detection which effectively solves the problem of sensitive illumination change which leads to more background noises. It focuses on the time-consuming processes.The main motivation behind performing this tasks in the wavelet domain is the noise resilience nature of wavelet domain, as the lower frequency sub-band of the wavelet transform has the capability of a low-pass filter. The other motivation is that the high-frequency sub-bands of wavelet transform represent the edge information, that provides a strong cue to handle images occlusion problems.Background subtraction is based on effective moving object detection using Daubechies wavelet transform, frame differencing and background updates which work on the better result which lacked due to the varying light conditions, shadows, and other occlusions. In this paper, a simple and effective unimodal approach of background subtraction by exploiting the low sub-band characteristics of the object image in the wavelet domain is used. The Daubechies complex wavelet transform is used because it is approximately shift-invariant and has better directionality information with respect to DWT(Discrete Wavelet Transform).

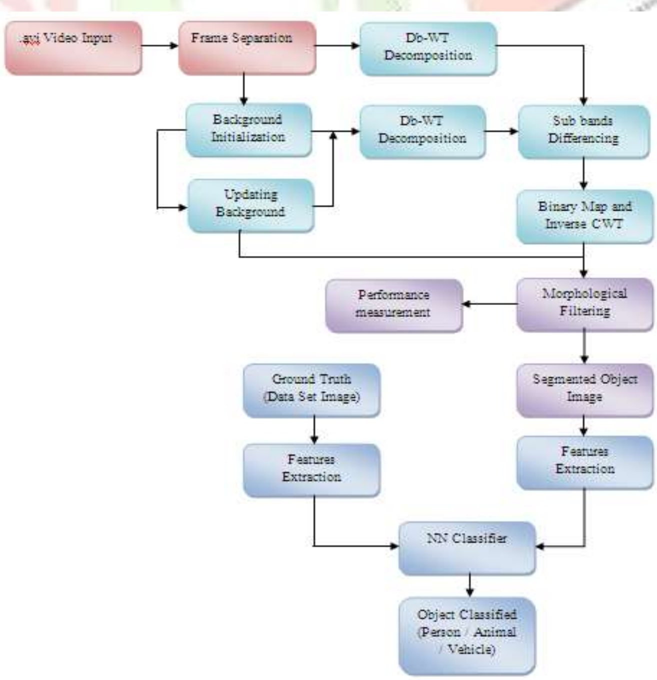


Fig. 3 Architecture of proposed system

IV. PROPOSED METHODOLOGIES

A. DAUBECHIES WAVELET DECOMPOSITION

Wavelet domain provides a framework to view and process image at multiple resolutions .We have used Daubechies Wavelet transform that has been used in various fields such as signal processing, image processing, computer vision, image compression, biochemistry medicine, etc. The proposed approach is broadly subdivided into three stages: background model-ling, moving object extraction using background subtraction.It provides an extremely flexible multi-resolution image and can decompose an original image into different subband images including low- and high-frequencies for image processing. Therefore the specific resolution data or subband images can be chosen by the people depending upon their own demands. After the decomposition of the original image into four-sub band images, it has to deal with row and column directions separately. First, the low-pass filter H and the high-pass filter G are exploited for each row data, and then they are down-sampled by 2 to get high- and low-frequency components of the row. Next, for each high- and low-frequency components of the column the high- and the low-pass filters are applied again and then are down-sampled by 2. During above processing, the four-sub band images are generated: HL, LH, and LL, HH. Each subband image has its own feature, such as the low- the LL-band preserves the low frequencies information and the high-frequency information is almost preserved in the HH-, HL-, and LH-bands. For the second level subband image the LL-subband can be further decomposed in the same way. By using 2-D DWT, an image can be decomposed into any level subband images.

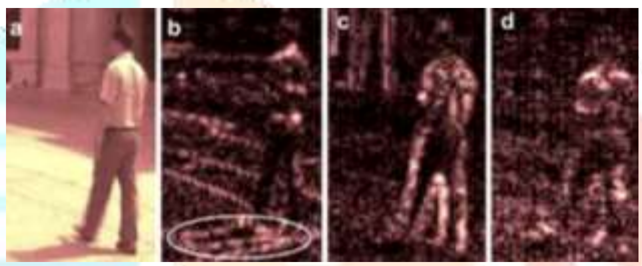


Fig 4. Wavelet decomposition of image from Video 1 (outdoor environment) (a) Approximation coefficients (b) Horizontal coefficients (c) Vertical coefficients (d) Diagonal coefficients

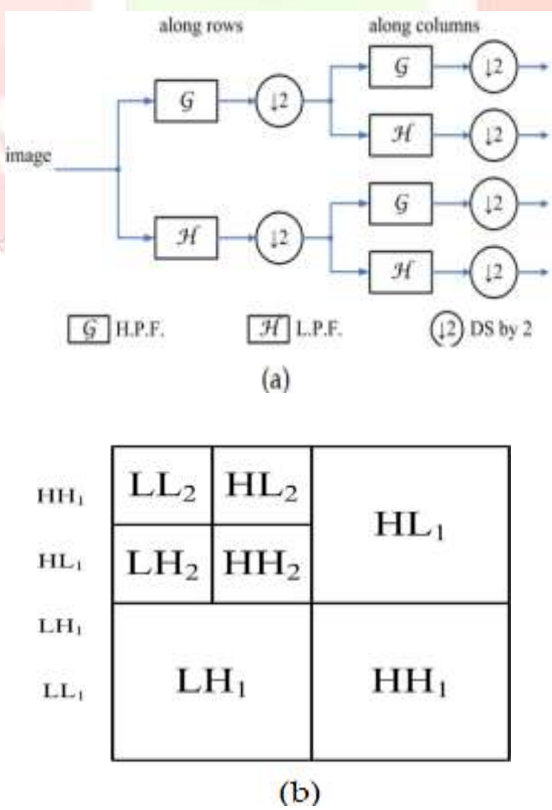


Fig 5 (a) Low pass and High pass frequencies subband (b) subbanding

B. BACKGROUND SUBTRACTION

Background subtraction method is a technique using the difference between the current frame and reference frame to detect moving objects. First, the reference frame image stored as a background image. Then the current image $f_k$with the pre-stored background image B, the subtraction process begins, and if the difference is larger than the bound threshold then is determined by the pixel to pixel on the moving target, or as the background pixel. The best choice of the threshold value of the background subtraction is important to achieve the success of motion detection . The small threshold the value will produce a lot of false change points, and the large threshold value will reduce the scope of changes in movement. The method formula is shown as :

$$R_k(x,y) = f_k(x,y) - B(x,y)$$

$$D_k(x,y) = \begin{cases} 1 \ \ background \ \ R_k(x,y) > T \\ 0 \ \ target \ \ R_k(x,y) \le T \end{cases}$$

The appropriate threshold value is adapted with the wavelength of the color, the changes of light conditions, so the choice of the dynamic threshold should be selected.

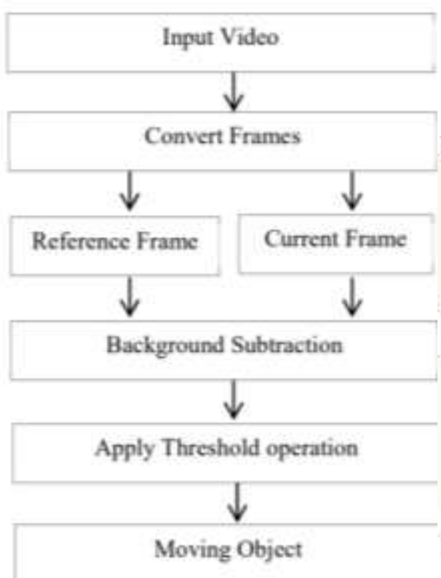


Fig 6. Flow Chart Of Background Subtraction Method

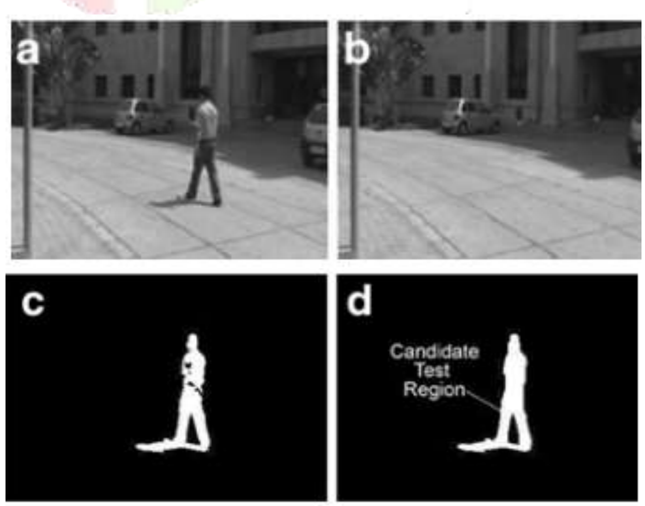


Fig 7. Moving object detection using background subtraction in complex wavelet domain (a) current frame (b) computed reference frame (c) background subtraction without morphological processing d) results after morphological processing.

C. FRAME DIFFERENCING

Frame difference method is also known as the adjacent frame difference method, the difference between the image sequence method etc.It refers to a very small time intervals Δt between the two images before and after the pixel based on the time differences, and then thresholding method to extract the image region of the movement, according to which changes in the difference of the specific flow chart as shownin Fig.

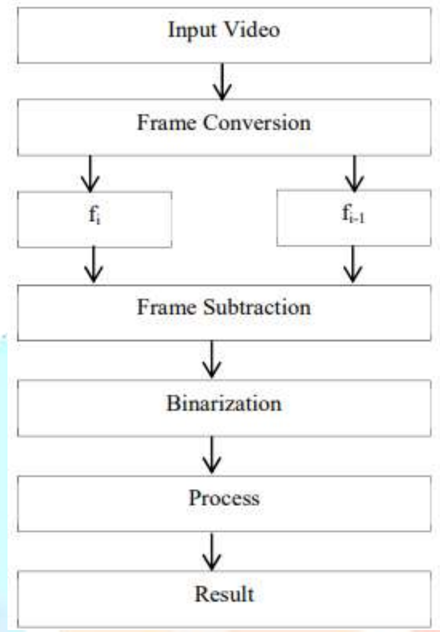


Fig 8. Flow Chart Of Frame differencing Method

The specific method of calculating the difference between the image Dk between the kth frame images $f_k$with the k-1 the frame image $f_{k-1}$is differential,fully differential and the negative differential , the corresponding formula is as follows:

Differential:

$$D_k = \begin{cases} f_k - f_{k-1} & if(f_k - f_{k-1}) > 0 \\ 0 & else \end{cases}$$

Negative Differential:

$$D_k = \begin{cases} |f_k - f_{k-1}| & if(f_k - f_{k-1}) < 0 \\ 0 & else \end{cases}$$

Fully Differential: $D_k = |f_k - f_{k-1}|$

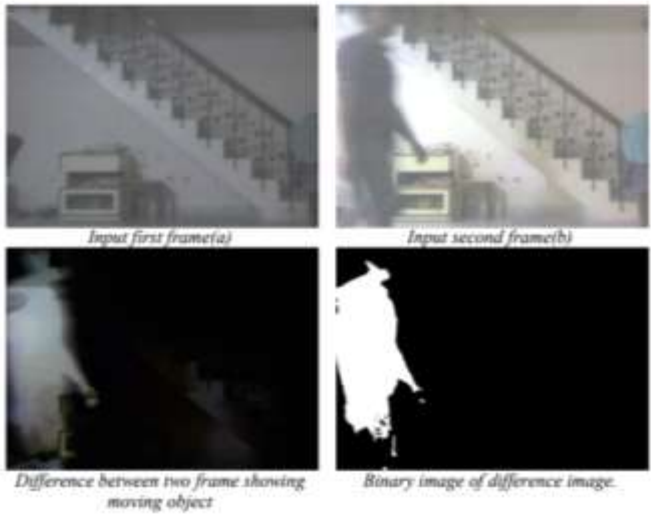


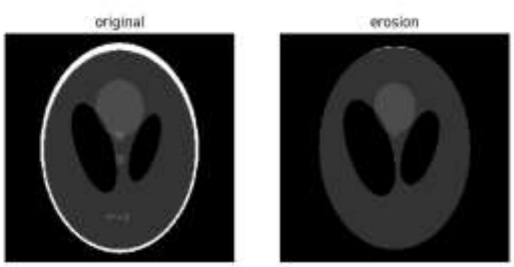
Fig 9. Frame differencing in binary images

D. MORPHOLOGICAL FILTERING

Morphological filtering is a collection of non- linear operations which compares the morphology of features of image, it is one of the most important steps in computer vision applications such as: medical analysis human-machine interface, robotics, traffic monitoring, and more. The Gaussian mixing model which is used for the background subtraction. For the pre-processing step, a smoothing method is used and a morphological filter was applied in order to solve the problem of background noise disturbance by removing unwanted pixels from the background.The filtering foreground segmentation twice with the same morphological structured element but with a different width was used to improve the accuracy of the result. All the methods used before have been effective but also have limits. Some of these methods when the number of frames is wide loses the object while others lose it when it changes direction or rolls at a high speed. In addition, the algorithms proposed for the detection of colors in RGB also lose their objectives when the object changes the color. But the proposed combination in this paper maintains contact with the object without losing it even if it changes direction or speed or the number of frame increases.

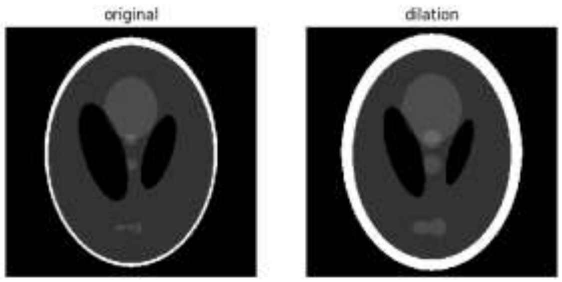
- **Erosion**

Morphological erosion sets a pixel to the minimum over all the pixels in the neighborhood centered at (i, j) . The structuring element, passed to erosion is a boolean array which describes the neighborhood centered at (i,j) . The white boundary of the image disappears or gets eroded as we increase the size of the disk around the structure. Also the size of the two black ellipses in the center increases and the disappearance of the 3 light grey patches in the lower part of the image.



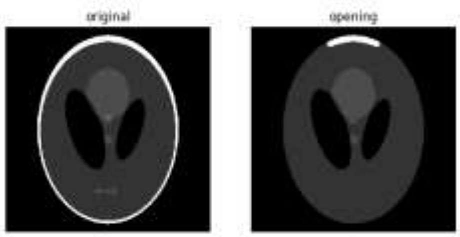
- **Dilation**

Dilation method sets a pixel to the maximum over all pixels in the neighborhood centered at (i, j). It shrinks dark regions and enlarges bright regions. As we increase the size of the disk, the white boundary of the image thickens or gets dilated. The thickening of the light grey circle in the center and the decrease in the size of the two black ellipses in the center, and and the 3 patches in the lower part of the image.



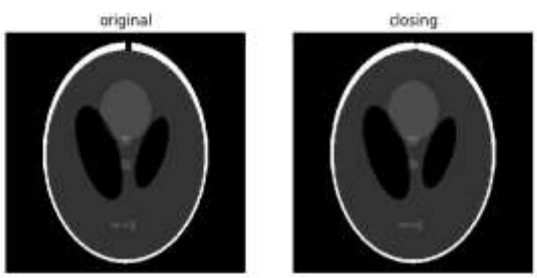
- **Opening**

Opening connects small dark cracks and can remove small bright spots (i.e. “salt”). The erosion operation creates the opening, light regions that are smaller than the structuring element are removed.The dilation operation ensures that light regions that are larger than the structuring element retain their original size. the light and dark shapes in the center retain their original thickness but the 3 lighter patches on the bottom get completely eroded.The parts of the outer white ring, which highlights the size dependence erases the part thinner than the structuring element, while the thicker region at the top retains its original thickness**.**



- **Closing**

Closing connects small bright cracks and can remove small dark spots (i.e. “pepper”).A dilation operation starts the closing on image, dark regions that are smaller than the structuring element are removed. The dilation operation ensures that dark regions that are larger than the structuring element retain their original size. The white ellipses at the bottom get connected because of dilation, but other dark region retain their original sizes**.**

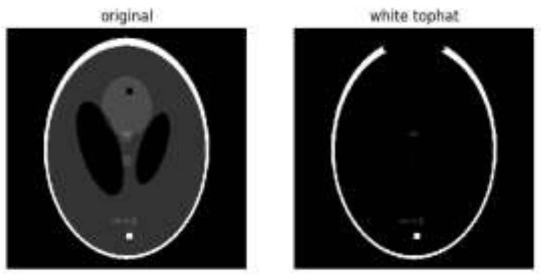


- **White Tophat**

As the image minus its morphological opening the white_tophat of an image is defined. The bright spots of the image that are smaller than the structuring element are returned.

```
   phantom = orig_phantom.copy()
   phantom[340:350, 200:210] = 255
   phantom[100:110, 200:210] = 0
w_tophat = white_tophat(phantom, selem)
plot_comparison(phantom, w_tophat, 'white tophat')
```

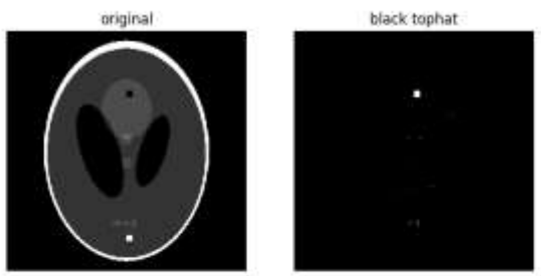
In the result, the 10-pixel wide white square is highlighted as it is smaller than the structuring element and the thin, white edges around .



- **Black Tophat**

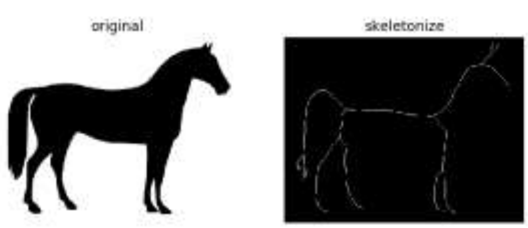
The black_tophat of an image is defined as the original image minus its morphological closing. The operation returns the dark spots of the image that are smaller than the structuring element.The wide black square of 10-pixel is highlighted as it is smaller than the structuring element.Many of these operations are simply the reverse of another operation. This duality can be summarized as follows:

1. Opening <-> Closing
2. Erosion <-> Dilation
3. White tophat <-> Black tophat



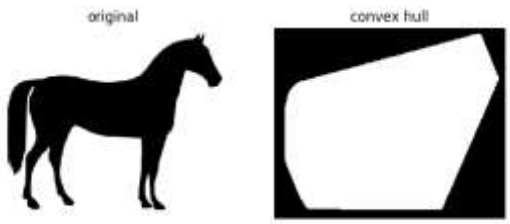
- **Skeletonize**

To reduce each connected component in a binary image to a single-pixel wide skeleton, thinning is used . It is performed on binary images only. This technique is used by applying thinning successively to thin the image to 1-pixel wide skeleton .



- **Convex Hull**

The convex hull image is the set of pixels include all white pixels in the input image surrounded by the smallest convex polygon. This is also performed on binary image. Convex hull image gives the smallest polygon which covers the white or True completely in the image. If we add a small grain to the image, we can see that convex hull adapts to enclose that grain.



E. PERFORMANCE MEASUREMENT

Measuring the performance of an object detection algorithm is one of the major tasks to validate the reliability and robustness of the detection algorithm. The evaluation of background subtraction and modelling methods can be performed in two ways i.e. qualitatively and quantitatively. The qualitative evaluation is based on visual interpretation, where as quantitative evolution requires a numeric comparison of computed results with ground truth data. Due to the necessity of computing a valid “ground truth”data, the quantitative evaluation of object detection is highly challenging. We have compared the performance of the proposed background subtraction approach with frame differencing method. Both qualitative and quantitative measures are used to compare the segmentations results. In order to provide a quantitative perspective we have used the false positive rate (FPR) and false negative rate (FNR). These measures are defined as:

The ground truth is generated by manually labeling the corresponding frames.

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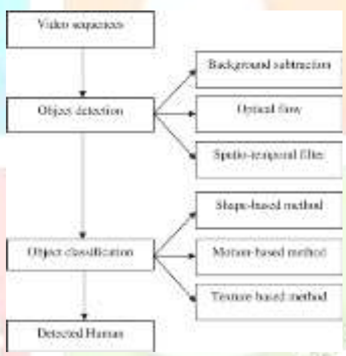

Fig 10. Flow Chart Of Performance Meaurement

V. EXPERIMENT AND RESULTS

An Input Video(.avi files) are converted into still images for processing it and detect the moving objects.These sequence of images gathered from video files by finding the information about it through ‘aviinfo’ command.

$$FPR = \frac{\text{the number of background pixels wrongly classified}}{\text{the number of background pixels in the ground truth}}$$

$$FNR = \frac{\text{the number of foreground pixels wrongly classified}}{\text{the number of foreground pixels in the ground truth}}$$

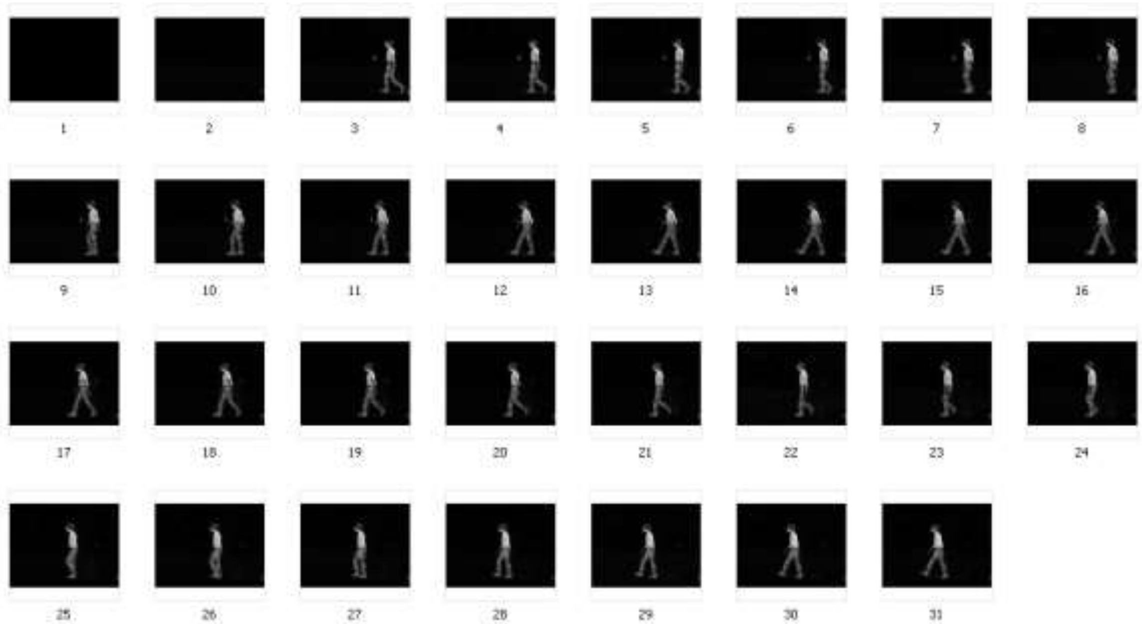

Fig 11. Binary images frame snapshot

These frames are converted into binary images with help of the command 'frame2im'. Create the name to each images and this process will be continued for all the video frames.

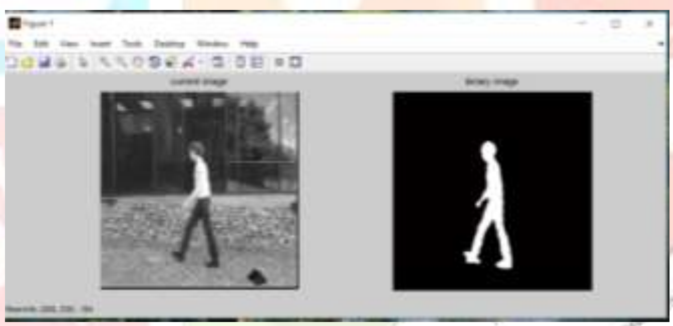

Fig 12. Result of converting grayscale image to binary

The moving object will be detected by frame subtraction and segmentation algorithms.The frame subtraction is done by subtracting current frame and previous frame for detecting object from background.The moving object extraction from subtracted frames is done by dynamic thresholding method for foreground detection.

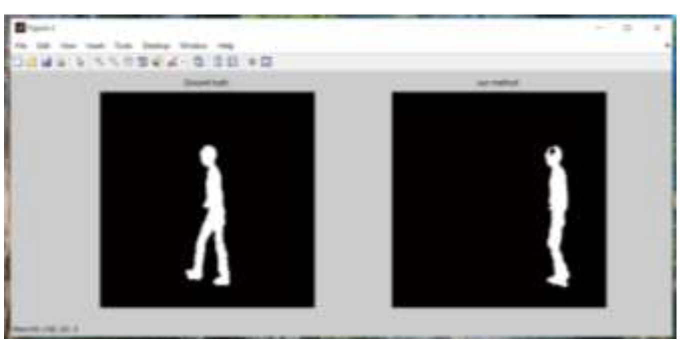

Fig 13. Frame Separation

Then background will be updated by comparing the process frame and background frame. This will be continued for all consecutive frames.After this process, morphological filtering will be applied for reducing background noise for accurate object detection. Using the daubechies wavelet decomposition method on the binary image frames, the performance measurement is calculated in terms of speed , accuracy in velocity, sensitivity, flexibility, and edge illuminations.

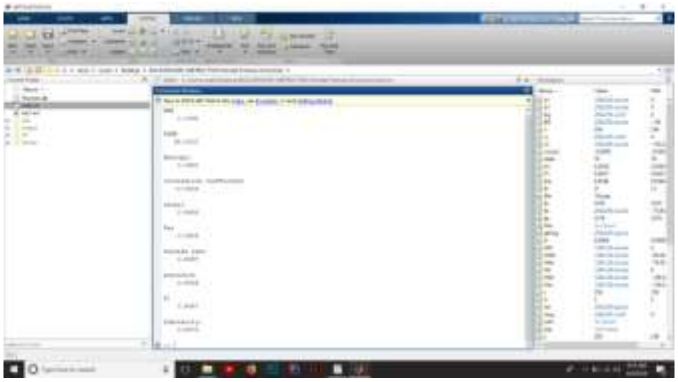

Fig 14. Performance Measurement

VI CONCLUSIONS

This work addresses the problem of background subtraction and modelling in complex wavelet domain based framework. In the discussed algorithm, pre-processing of image (the image is converted fom RGB to grayscale) is used to generate initial background model in a training stage and then foreground pixels are obtained by applying frame separation method (the image is divided into many frames) to the background subtraction scheme in the subsequent frames. The object detection results reveal that background subtraction in a wavelet domain provides noise removing capabilities, with the appropriate choice of the wavelet. Due to the Frame differencing method, we were able to detect mobility of object therefore helps in separating the foreground and background by the sequences of the frames of any image. The decomposition method has been tested on widely differing frames of the image. Once after taking the differences, the morphological filtering is performed on the frames during the background updating to remove edge occlusions and background noises. The comparison between the different frames with the reference or the ground truth set data ,to measure the performance of the object and the result reveals the clear information about the object .

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