REAL TIME PEDESTRIAN DETECTION AND TRACKING FOR DRIVER ASSISTANCE SYSTEMS

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REAL TIME PEDESTRIAN DETECTION AND TRACKING FOR DRIVER ASSISTANCE SYSTEMS

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Bachelor of Technology in "Electrical Engineering"

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CERTIFICATE

This is to certify that the thesis titled "**Real time pedestrian detection and tracking for driver assistance systems**", submitted to the National Institute of Technology, Rourkela by **Mr. Swaraj Preet Swain, Roll No**: **109EE0310 and Mr. Srilokanath Dalai, Roll No: 109EE0265** for the award of Bachelor of Technology in Electrical Engineering, is a bonafide record of research work carried out by him under my supervision and guidance.

The candidates have fulfilled all the prescribed requirements.
The draft report/thesis which is based on candidates' own work, have not submitted elsewhere for a degree/diploma.

In my opinion, the draft report/thesis is of standard required for the award of a Bachelor of Technology in Electrical Engineering.

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ABSTRACT

Real time pedestrian detection and tracking is considered as a critical application. Night time driving is more risky as compared to day time driving because of poor visibility especially in the case of senior citizens. While traditional methods of segmentation using thresholding, background subtraction and background estimation provide satisfactory results to detect single objects, noise is produced in case of multiple objects and in poor lighting conditions. To overcome these difficulties, a new method is proposed for detecting and tracking multiple moving objects on night-time lighting conditions. The method is performed by integrating both the wavelet-based contrast change detector and locally adaptive thresholding scheme. In the initial stage, to detect the potential moving objects contrast in local change over time is used. To suppress false alarms motion prediction and spatial nearest neighbor data association are used. A latest change detector mechanism is implemented to detect the changes in a video sequence and divide the sequence into scenes to be encoded independently. Using the change detector algorithm (CD), it was efficient enough to detect abrupt cuts and help divide the video file into sequences. With this we get a sufficiently good output with less noise. But in some cases noise becomes prominent. Hence, a method called correlation is used which gives the relation between two consecutive frames which have sufficient difference to be used as current and previous frame. This gives a way better result in poor light condition and multiple moving objects.

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LIST OF SYMBOLS

1) S90,S45,S135 …….3x3 SOBEL KERNEL MATRIX

2) Vthres …….vertical thresholding value

3) Hthres……..horizontal thresholding value

4) Dv…….vertical distance between blobs

5) Dh……horizontal distance between blobs

6) X_k…… the state vector with *n* dimensions

7) Z_k…… the measurement vector with *m* dimensions

8) A……state transition matrix

9) H…….measurement matrix

LIST OF FIGURES

CHAPTER I:

INTRODUCTION AND REVIEW

1.1 PROJECT OBJECTIVE: Real time pedestrian detection and tracking for driver assistance systems

Applying image processing techniques to pedestrian detection and tracking has been a hot focus of research in Intelligent Transportation Systems (ITS) in the last decade. Automatic pedestrian detection [1] increases the safety and efficiency of traffic management and control. For example, pedestrians have to press a push button in order to get the walk signal at signalized intersections conventionally, while automatic pedestrian detection system can detect the presence of pedestrians and allocate green extension signal to ensure the pedestrians have enough time to cross the street.

However, tracking of moving pedestrian is a challenging task [2], because pedestrians are not moving rigid bodies and often carry some movable possessions such as bags and umbrellas and several other things. Therefore, the tracking of pedestrian is more complex than that of moving rigid bodies.

In human tracking, the tracking algorithms can be categorized into four groups [3]: region-based, contour-based, feature based and model-based. The first three groups suffer from a common disadvantage in handling occlusions, while the model-based tracking algorithms are very consuming and could not be used in real time. But recently condensation algorithm [4] and mean shift algorithm [5] have shown some advantages in solving occlusion problem. However, due to many of the solutions proposed by these methodologies are computationally very expensive, Kalman filtering is still the most commonly used algorithm for tracking. This paper presents a new robust method for pedestrian tracking. This approach includes three steps: pedestrian detection, feature extraction and pedestrian tracking. Firstly, Gaussian Mixture Model (GMM) is used in

object detection. For every foreground image grabbed by implementing the concept of moving segmentation, various preprocessing filters are applied to remove noisy pixels from the image. Then, 3 types of features are extracted from the image, including spatial position, shape and color information. At last, the segmented pedestrians in the current frame are associated with the objects detected in the previous frame.

1.2 MODELLING METHODS

1.2.1 THRESHOLDING

Thresholding is based on a clip-level or value to turn a gray-scale image into a binary image. It is the simplest method used for image segmentation. This method is carried out by first selecting a threshold value (or values in case of multiple-levels are selected) which is optimum. In industry several popular methods are used, including the maximum entropy method, Otsu's method (maximum variance) etc.

1.2.2 BACKGROUND SUBTRACTION

We use only the successive I-frames for tracking in our algorithm and thereafter interpolate the object motion in the intermediate frames. We initially acquire a DCT image of an I-frame representing the background that is treated as the reference image. After that, all subsequent DCT images are compared with the reference image to segment the foreground object. The basic concept of this method is that two successive frames are subtracted to extract the foreground image. This method is generally used only when the background is non-movable. Based on the model of the application the background image

is created and is updated from time to time whenever there is a permanent change in the background.

1.2.3 BACKGROUND ESTIMATION

In this technique, the algorithm identifies the incomplete background as those pixels that do not belong to the foreground pixels. As the foreground objects continue moving, the background estimation algorithm estimates more and more of the background pixels. Once background estimation is completed by the program, the background is subtracted from each video frame to produce foreground images. This foreground image which is generated is then converted to binary image. This is carried out by implementing the technique of thresholding and performing blob-analysis and other morphological closing on each foreground image. Then object tracking is carried out by another program.

1.2.4 OPTICAL FLOW

Multiple methods allow computing by the optical flow method among which partial differential equation based methods, gradient consistency based techniques and least squared methods are very popular. In this model we have used an optical flow estimation technique to get an estimation of the motion vectors in each frame of the video sequence. Then the required moving object is detected by a program block and converted into binary image. This is carried out by implementing thresholding and performing blob-analysis and other morphological closing on each foreground image. Then object tracking is carried out by another program.

1.2.5 ADAPTIVE CONTRAST DETECTION

This method is effectively used basically for detection and tracking multiple moving objects at night-time lighting conditions and dull light conditions. Normalized cross-correlation is used to remove effect of global changes in the lighting form one frame to another frame. First of all potential moving objects are detected by using contrast change in local change over time. Motion prediction and spatial nearest neighbor data association is used to suppress false alarm due to minor contrast change. After this program is executed we get a contrast image which contains the moving objects. This contrast image is converted to binary image. This is done by implementing the technique of thresholding and performing blob-analysis and other morphological closing on each foreground image. Then object tracking is carried out by another program.

1.2.6 EDGE DETECTION

In images of a road, the pedestrians are present only in a limited region in the image frame. Hence, it is not necessary to process the entire frame. An ROI where probable pedestrians could be found in the image is chosen for processing. The edge detection is performed using a 3x3 Sobel kernel for vertical and diagonal edges (45 degrees and 135 degrees).

$$S_{90} = \begin{Bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{Bmatrix}$$

$$S_{45} = \begin{Bmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{Bmatrix}$$

$$S_{135} = \begin{Bmatrix} 0 & -1 & -1 \\ 1 & 0 & -1 \\ 1 & 1 & 0 \end{Bmatrix}$$

S45, *S90* and *S135* are the kernels used for obtaining edges along the vertical and diagonal (45o and 135o) directions respectively. For each pixel in the input frame, the value obtained after applying each of the 3 edge kernels is compared .On the edge image obtained from above, a morphological opening operation is performed using a vertical kernel of height 3 pixels and width 1 pixel. The opening operation removes very small edges from the image which arise usually due to noise. The output image now consists of only the prominent candidate vertical edges. Fig. 2 shows a sample output of the proposed candidate vertical edge detection method. One can notice that the output consists of only vertical edges and does not contain any noisy edges, since they are eliminated by the opening operation.

1.2.7 BLOB DETECTION AND MERGING

The blob detection scheme identifies all the pedestrian-like objects in an image using connected component labeling. It comprises of generating a data structure to save information about each blob. Blobs which fall within the predefined dimension criteria are retained and the small sized blobs which are generally noise pixels are removed at this stage. Vertical edges located close to each other, usually belong to a single object in an image. In cases where the pedestrian is located very close to the camera or is running, the edges of the same pedestrian are separated by a distance. In such cases the blobs are separated. As a result, there is a possibility of losing pedestrians, because the individual blobs may not independently satisfy the dimension criteria. Merging of blobs is necessary to combine all the edges belonging to one pedestrian. This improves detection accuracy and reduces missed detections. Merging of blobs is done as follows- Let Dv and Dh be

vertical and horizontal distances between centroids of adjacent blobs respectively. Blobs that satisfy the condition given below are merged together.

Dv < VThresh and Dh < HThresh.

1.2.8 ENHANCEMENT OF IMAGE BLOCKS

The image blocks from the original image, corresponding to the output blocks from the above step, are called as candidate blocks. Each of the candidate blocks may contain a pedestrian along with some non – pedestrian information like background. An enhancement technique is used to boost the intensity of a probable pedestrian in the candidate block. For this purpose, a pedestrian edge value is calculated by taking an average of all pixel values from original image that belong to edges in the candidate block. A pear shape-like curve is then applied on the candidate block to suppress the brighter values and darker pixel values while boosting only pixel values 'of interest' i.e. pedestrian pixel values. This curve is applied only when 70% of image block contains pixels with intensity values less than a predefined constant (this constant value is decided from the image brightness). Due to the use of pear shape-like curve, the problem of saturation, observed for nighttime images, especially, in regions of the image having inherently higher pixel values, is reduced. Also, the image contrast and overall image quality is improved, which is useful for the intensity profiling step that follows.

1.2.9 PROFILING

The output of the method explained in previous section gives image blocks which are probable pedestrian candidates. The merged blocks are not necessarily tight bound boxes

and may contain more than one pedestrian. In order to further segment the boxes to extract individual pedestrians, intensity profiling is used. Intensity profiling uses a summation of intensities along rows or columns of an image. In this step, we employ both horizontal and vertical profiling. For row profiling, sum of pixel intensities belonging to each column is stored in respective bin. In case of column profiling, each bin contains the sum of pixel intensities belonging to each corresponding row. The row profile has number of bins equal to the columns in the image, while the column profile has number of bins equal to the total rows in the image. The row and column profiles are used for calculating the width and height respectively, of an object in the image block in terms of number of pixels. This is done by calculating the number of rows (or columns) for which the bin values lie above the profiling threshold.

1.3 THESIS OBJECTIVES

1) To study the various modeling methods such as thresholding, background subtraction, background estimation etc.
2) To implement the various modeling techniques in a particular image frame or taking a snapshot from a video sequence.
3) To detect a person from a particular image frame.
4) To detect certain features of the person in the particular image frame like the eyeglasses etc.

CHAPTER II:

METHODOLOGY

2.1 THRESHOLDING

Thresholding is the simplest method of image segmentation. Thresholding is used to create binary images from a gray-scale image. In the thresholding process, depending on their values, individual pixels in an image are marked as "object" pixels if the value is greater than some threshold value (assuming an object to be brighter than the background) else the pixels are marked as "background" pixels. There are various conventions such as threshold above, threshold below, threshold inside and threshold outside. In our case we have used “threshold above” convention. The value “1” is assigned to object pixel while value “0” is assigned to background pixel. Then a binary image is constructed by coloring each pixel according to the values assigned to them. Different thresholding techniques are available on the basis of information and algorithms. Thresholding can be classified as bi-level and multi-level. In bi-level thresholding, the pixels are classified into two groups, one containing the pixels having gray levels above the threshold and the other with gray levels below the threshold. Multiple thresholds are present in multilevel thresholding. Pixels are grouped having gray level within a threshold.

2.2 ADAPTIVE CONTRAST DETECTION

The method of adaptive contrast change detection **[6]** for video object tracking essentially involves integrating both the wavelet-based contrast change detector and locally adaptive thresholding scheme. This is preferred for night surveillance **[7]** and multiple colored objects **[8]** tracking. The first step includes computing the contrast in local change over time which is used to detect potential moving objects. This is followed by motion

prediction and spatial nearest neighbor data association which helps to suppress false alarms.

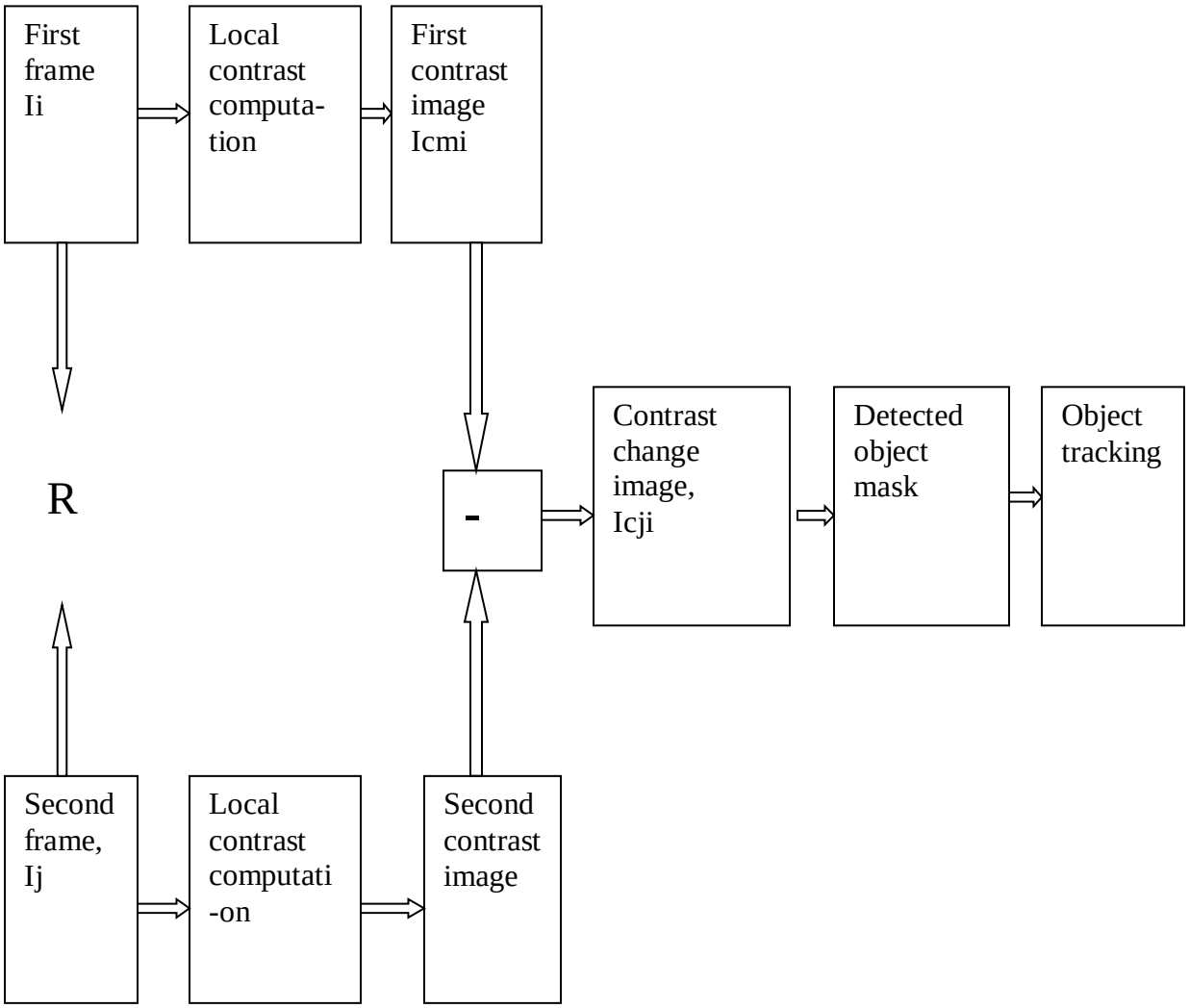

Fig 2.1: Algorithm for object detection using adaptive contrast change

2.3 MOTION DETECTION AND OBJECT TRACKING

2.3.1 CHANGE DETECTOR AND SEQUENCE TESTER

A new change detector is used to detect changes in a particular video sequence, which is further divided into scenes to be encoded independently. It is then enhanced using a sequence tester to test each scene for high activity (arising due to motion) and thus decide whether or not another reference (key) frame is required. The performance of the suggested method is checked with the help of simulation results. This mechanism is based on segmentation of the video into scenes using a change detector wherein one or more key frames are chosen for each scene.

A scene is a sequence of shots that belong together semantically. According to the length and properties of the scene, the numbers and locations of the key frames are chosen. Each of the other frames is then differenced from the nearest key frame. In a scene, there exist two types of shot boundaries in videos: abrupt shot changes called "cuts", and gradual transitions between two different shots. The proposed scene cut detector here is simple and fast. The detector divides the whole video into independent sequences to be encoded separately which is accomplished in two steps. Firstly, the video as a whole is used to get the global cuts, thus dividing the video into sequences which is the output of the change detector (CD). Secondly, each sequence is investigated to ensure that there is not any high level of changes between the frames that may cause artifacts in the decoded video. The results are good since complexity involved here is low and this module in the code boosts efficiency further.

The change detector uses the normalized sum of absolute differences (SAD) between each two successive frames on a pixel-by-pixel basis. If this difference normalized difference is high, then an abrupt cut is present. The various conditions and effects are as follows:

- If the normalized difference is low, then cut type is continuous.

- If the normalized difference is in between, then cut type is gradual change.

- If the normalized difference is high, then cut type is abrupt change.

The change detector algorithm (CD) gave efficient results to detect abrupt cuts and helped divide the video into sequences. However in the case of long scenes (where motion occurs), there is a high level of changes between frames which must be considered which is because of the fact that the detector is based on the concept of differencing frames i.e. for each scene, a key frame is chosen and all other nearby frames are differenced from it. In case of long scenes with high level of changes between frames especially those with respect to the key frame, the encoded frame carries huge information which may be lost due to lousy encoding and decoding and there arises the need for another key frame. Here, a key frame is chosen for every scene and all the other frames are differenced from it. The change detector algorithm thus helps to determine the gradual change and abrupt change.

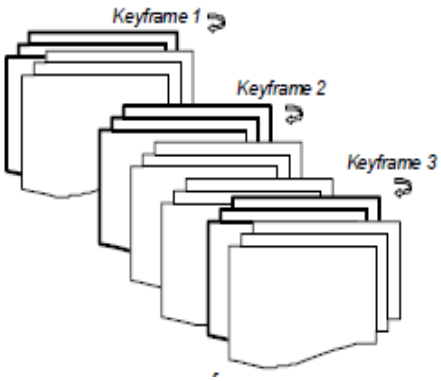

Fig 2.2: Key Frames

2.3.2. ALGORITHM: OBJECT DETECTION AND TRACKING

The algorithm for object detection involves two steps. In the first step, local contrast computed over the entire image detects the object. In the second step, the detected objects are tracked and the falsely detected ones are removed using a feedback mechanism from the tracking algorithm. Here, we assume I as the image frame, R as the inter-frame relation which describes the similarity between two frames, T1 the contrast threshold and T the contrast change (CC) threshold. Contrast Change (CC) Image ICji is calculated between every two successive frames, which are deployed for object mask detection, which in turn is used for object tracking.

2.3.3 LOCALLY ADAPTIVE THRESHOLDING

This class of algorithm involves calculating a threshold at each pixel, which is based on some local statistics like range, variance, or surface-fitting parameters of the pixel neighborhood. In what follows, the threshold T (i, j) is denoted as a function of the coordinates (i, j) at each pixel.

2.4 THRESHOLDING TECHNIQUES AND CODES

2.4.1 COLOUR BASED DETECTION

In this method of detection if there are objects which are different in color then we can detect a particular color by simple methods . The following matlab code first reads the image and then returns a binary image in which the green pixels are replaced by white and the rest by black.

2.4.2 EXTRACTING PROPERTIES FROM THE IMAGE

There are certain features in the image which need to be extracted to locate and detect the particular object. Some of the features are centroid,area etc. The following code in matlab extracts area and centroids of the image.

```
>> im=imread('pedestrian1.jpg');
>> img=im2bw(im);
>> [b,l]=bwboundaries(img,'noholes');
>> stats=regionprops(l,'Area','Centroid');
```

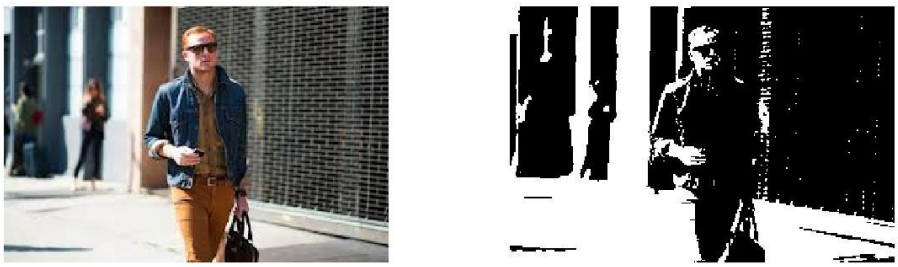

Fig 2.3: Estimating the area and the centroid of the pedestrian

2.4.3 FEATURE EXTRACTION FROM INFRARED IMAGES

The following sections explore the different properties of visible and infrared images, and pursue how the differences will have impacts on pedestrian detection algorithms, i.e., the pro and cons for pedestrian detection.

2.4.3.1. PROPERTIES OF INFRARED IMAGE BRIGHTNESS

The function of infrared detectors is to sense infrared radiant energy incident on it and to produce electrical signals proportional to the temperature of target surfaces. The brightness intensities of infrared images are representative of the temperature of object surface points. In general, infrared images have the following properties that differ them from visible images. First, pedestrians usually emit more heat than static background objects, such as trees, road, etc. Therefore image regions containing pedestrians or other "hot" objects will be brighter than background. Secondly, since the temperature of all pedestrians' bodies is similar, the brightness of different pedestrians in different infrared images should be similar in spite of different color and textures of their clothing. Thirdly, the intensities of whole pedestrian regions should be uniform approximately since the temperature of different body parts is similar. Up to now, the above properties are the advantages of infrared images over visible images for pedestrian detection. In comparison, intensity value of visible images varies significantly among different people and among different body parts based on clothing information. The fourth property of infrared images is that intensity value depends also on other factors besides temperature, such as object surface properties (emissivity, reflectivity, transmissivity), surface direction, wavelength, etc. In typical infrared images, the intensity value for a pole in the

upper part is higher than in the lower part. For pedestrian regions, body-trunk-regions are darker than head-regions and hand-regions. The whole pedestrian regions are composed of several non-uniform bright and dark areas. The last property of infrared images is that image intensities are clustered in small regions in image intensity histogram, while intensity histogram for typical visible images is close to constant for better utilizing the dynamic range of intensity value. Compared with rich and colorful visible images, infrared images are blurrier, have poorer resolution and clarity, and foreground/ background contrast is less clear.

2.4.3.2 THE IMPACT OF INFRARED IMAGES PROPERTIES ON PEDESTRIAN DETECTION FEATURE CHOICE

Infrared-based pedestrian detection applications can inherit some features for visible image-based pedestrian detection **.** For example, infrared stereo cameras are introduced in night vision systems for depth information similar to the stereo systems introduced in vision system. Another example is w here support vector machine is introduced to train classification algorithms based on intensity value of pixel-array for ROIs. However, some properties of infrared images introduce challenges in pedestrian detection and limit the performance of reusing the features mentioned. First, because of the imaging principle and poor resolution of infrared images, it is almost impossible to extract a few component features unique to human beings, such as skin hue, eye location, face, etc., from infrared images. It is also hard to detect clear contours of pedestrians as used in and and we cannot use contour-based templates to detect pedestrians at different poses. Similarly, geometric model of human parts is seldom used since it is hard to capture so many

descriptive details for pedestrians, especially for real driving situations where scenes change rapidly. Secondly, lacking in sufficient image texture and low image contrast lead to less reliable corner-based feature points.

On the other hand, the unique properties of infrared images introduce several special features to simplify infrared-image-based pedestrian detection. For example, the brightness of pedestrian regions in infrared images can be treated as detection features. Theoretically, intensity value of all pedestrian regions in infrared images should be uniform in whole regions, invariant for different pedestrians and in different seasons. Based on these features, probability-based template and pedestrian detection by searching for heads (whose images are round, uniformly bright regions) while assuming flat road**.** These unique features provide convenience for pedestrian detection, while at the same time they might encounter the following challenges in real applications. First, other "hot" objects than pedestrians, such as vehicles and poles, produce regions that might be as bright as or brighter than pedestrians' regions. In summer, other background objects, such as hot road surfaces, might also introduce many bright regions in infrared images. This implies that segmentation cannot depend on high intensity value alone, or else error in pedestrian detection is unavoidable. Secondly, since whole pedestrian regions are composed of several non-uniform bright and dark areas, we cannot simply employ uniform template models.

2.5 TRACKING

Pedestrian tracking is to determine the pedestrian correspondences between frames. In order to real-time track moving pedestrian, our approach works in two stages: prediction

step and matching step. The prediction step is to determine the search area in which the pedestrian might be seen in next frame. A search window is defined for each precious object, which centers on its predicted centroid and has an area adapted to the scale of the measurement error in the Kalman model. The matching step is to search the corresponding object in the predicted area. The feature vectors of detected pedestrians in the search window are compared with integrated templates. If a matching case is found, the relation between objects in two consecutive frames would be recorded.

2.5.1. PREDICTION

In order to reduce the cost of search operation, the Kalman Filter is used to predict the location of pedestrian in next frame. The Kalman filter model is composed of system state model and measurement model as follows:

$$x_k = A.x_{k-1} + B.u_k + w_k \qquad (1)$$

$$z_k = H.x_k + v_k \qquad (2)$$

where X_k is the state vector with *n* dimensions; Z_k is the measurement vector with *m* dimensions; X_k is the control vector; *A* and *H* are the state transition matrix and measurement matrix respectively. W_k and V_k are random variables representing the process and measurement noise.

2.5.2. MATCHING IN THE PREDICTED AREA

In previous frame, we draw a bounding box around a detected pedestrian and get the corresponding centroid which is used to define extended search windows in the current

frame. The size of search window is obtained by adding measuring errors to the length and width of their corresponding bounding box in the previous frame. The candidate matched pedestrians are those whose bounding boxes intersect the search window.

CHAPTER III:

RESULTS

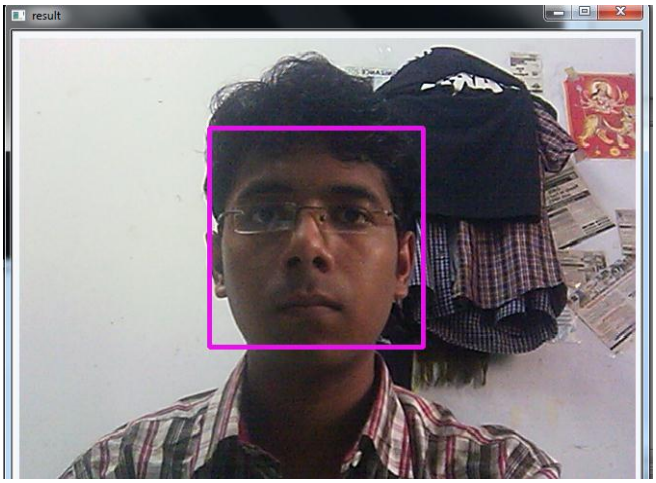

Fig 3.1: Face detection

The above figure detects the face in the image frame by using the methodology discussed above. In order to extract some special facial features certain algorithms are used . The following figure shows that the eye glasses are detected in the particular image frame.

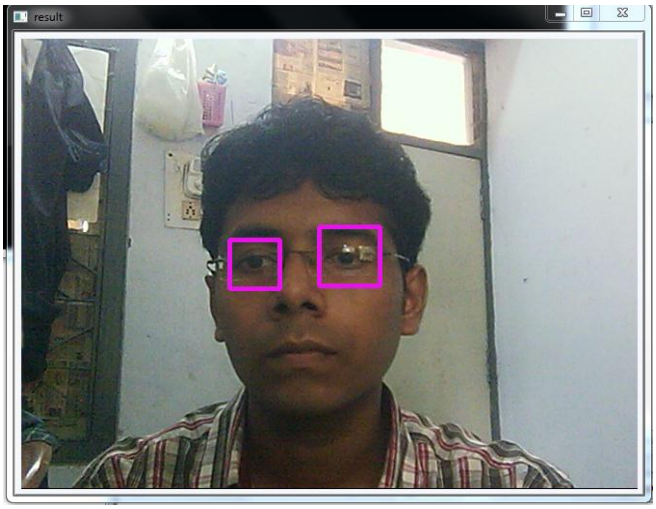

Fig 3.2: Eye glasses detection

Along with the special feature detection we also have to detect the upper body portions and the lower body portions of the pedestrians. The following figures depict that.

Fig 3.3 : Lower body detection

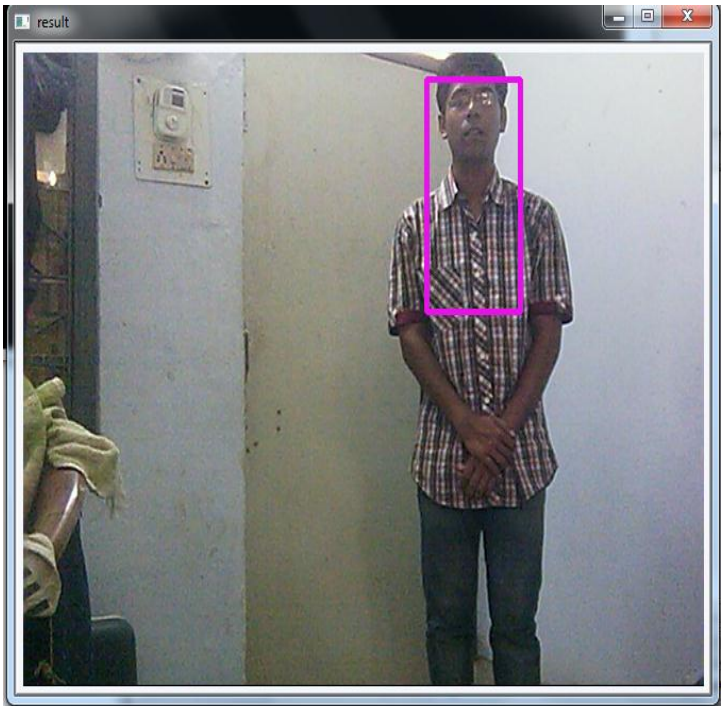

Fig 3.4: Upper body detection

There are certain disadvantages of this method. In this method if we want to track a particular object then it is not possible. Due to the global thresholding method used in this approach it detects multiple objects of the same nature. Again this method also couldnot respond to the occlusion problems. Again one of the major disadvantage of this method is that it may detect several other objects along with the pedestrians in real time. For example a pedestrian walking on the road with dog , the dog may be detected along with the pedestrian.

Fig 3.5: Background subtraction image showing a car in the frame(foreground is white)

Fig 3.6: The background subtraction image showing car at a different location

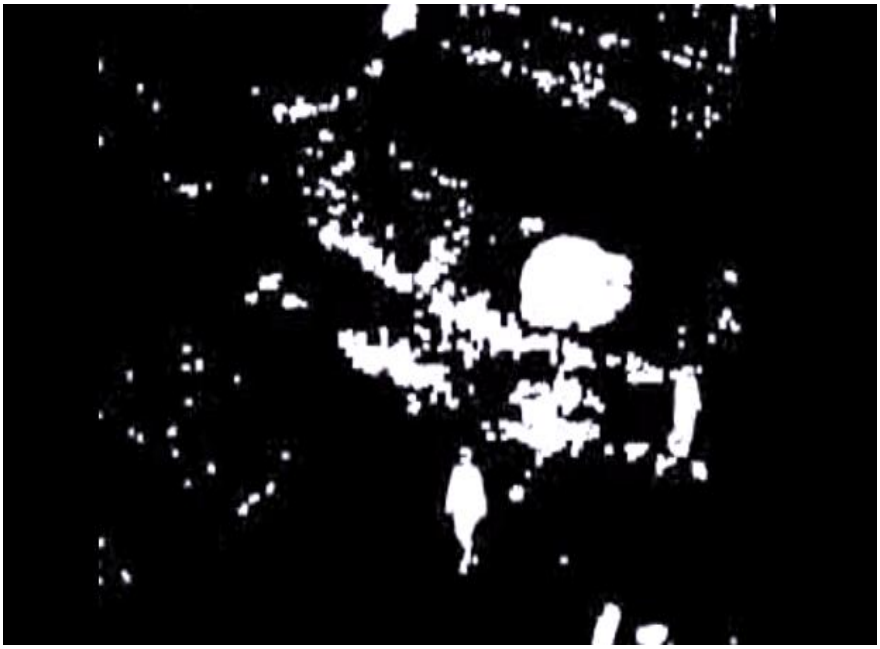

Fig 3.7: The background subtraction image showing two pedestrians and a car

CHAPTER IV:

CONCLUSIONS AND FUTURE WORK

4.1 CONCLUSION

The objective of this project is to detect and track pedestrians for driver assistance systems. Tracking and detection at night time is also considered in this paper. Night time tracking and detection is not that easy due to poor lighting conditions. So certain algorithms have been used to detect and track like the adaptive contrast detection method. Now for the time being we just have started the process in which we can detect objects by the algorithms mentioned in the report. We shall start the process of tracking that too at night time as soon as possible. The latest method of Adaptive Contrast Change Detection gave satisfactory results in sufficiently reducing the noise while detecting multiple objects. But in some cases it gives unwanted noise. Hence, we shall use correlation which basically gives the relation between to frames having significant contrast change. Use of correlation has significantly improved the output and gives better result even with multiple moving objects. The approach seems to have efficient practical applications in poorly-lighted conditions such as night-time visual surveillance systems.

4.2 FUTURE WORK

There is lot of scope in the field of pedestrian detection and tracking during night time especially. In the work done above there are disadvantages as mentioned above. In the above method there is multiple detection in a particular image frame consisting of similar features . If the objective is to detect a particular pedestrian then the above method fails. Therefore future work can be done in this field. Since in the detection and tracking of

pedestrians at night time involves infrared images so special algorithms and techniques need to be devised in the near future.

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