Deep Learning Based Object Recognition in Real Time Images Using Thermal Imaging System

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Abstract. An efficient driver assistance system is essential to avoid mishaps. The collision between the vehicles and objects before vehicle is the one of the principle reason of mishaps that outcomes in terms of diminished safety and higher monetary loss. Researchers are interminably attempting to upgrade the safety means for diminishing the mishap rates. This paper proposes an accurate and proficient technique for identifying objects in front of vehicles utilizing thermal imaging framework. For this purpose, image dataset is obtained with the help of a night vision IR camera. This strategy presents deep network based procedure for recognition of objects in thermal images. The deep network gives the model understanding of real world objects and empowers the object recognition. The real time thermal image database is utilized for the training and validation of deep network. In this work, Faster R-CNN is used to adequately identify objects in real time thermal images. This work can be an incredible help for driver assistance framework. The outcomes exhibits that the proposed work assists to boost public safety with good accuracy.

Keywords. Thermal Imaging, HSV color space Segmentation, Faster Region-Convolution Neural Network (Faster-RCNN), Region Proposal Network, Intersection over Union (IoU).

1. Introduction

Driver assistance frameworks are probably the important applications object recognition. Individual in front of vehicles face a high danger of injury or demise during the night or because of restricted perceivability. Having a warning framework [1] to hinder interlopers is pivotal for both the safety of public and to avoid monetary losses. To forestall the mishaps, several intelligent frameworks have been created utilizing close circuit TV cameras combined with machine learning innovations [2]. However, most frameworks [3] work along with database of images captured in proper light, while the detection performance in front of vehicle in the restricted perceivability [4] is extensively more awful. In thermal imaging system, the radiations as infrared light are detected by the device called thermal camera to capture the thermal images. To recognize individuals in the restricted perceivability, several investigations have

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adopted machine learning based methods [5] utilizing thermal IR images. The machine learning based approaches can be distinguished on the basis of feature descriptors & classifiers such as HOG[6], SIFT[7], INERTIA[8], SVM [9][10] or Adaboost [11].

In some human recognition applications haar feature based classifiers [12][13] is used for thermal IR images. Although the machine learning methods [14] performs satisfactorily but for images having noisy/ ambiguoused features[15] suffer from degraded performance. To handle this problem convolutional neural network [16] [17] based deep learning methods [18] have been used for object recognition in thermal images. The recognition performance for thermal images can be upgraded using deep network based methodologies [19]. It has observed that human detection methods based on CNN [20][21] give better recognition results as compared to methods based on SVM. The selection of proper training data affects the recognition performance of deep network methods[22]. Several investigations have created thermal image datasets, e.g. CVC-14 [24], LSI [25] and KAIST [23] for person recognition in limited visibility. The work presents a precise as well as proficient strategy to recognize objects in real time thermal images. In this paper, a system is intended to segment the moving objects from the image using color HSV segmentation. Finally, the Faster-RCNN is utilized to distinguish the objects in the real time thermal images. This paper is organized in various subsections as: section II presents the proposed procedure in detail including collection steps using thermal imaging, HSV segmentation and deep network (Faster R-CNN) for recognition of object. The outcomes and discussions are explained in section III. Finally, the conclusion of paper is discussed in the section IV.

2. Proposed method

The proposed method is used to recognize the object on it from scene sequence captured by the thermal camera [27]. The basic block diagram of the proposed work is illustrated in figure 1. The “VINCENT HD and Night vision IR camera” as shown in figure 2 acquires the video sequence with the resolution of 720p in night vision IR camera mode. The frames are extracted from the video sequences for the further processing. The various steps of the proposed approach for the recognition of the objects are illustrated in algorithm 1 and discussed in the following subsections.
2.1 Object Recognition

For the real time identification of the objects in the thermal images extracted from the video sequence by the “VINCENT HD and Night vision IR camera: Initially the noise (unwanted surroundings) is removed from the image and then objects are identified using Faster R-CNN [28] network.

Figure 2. The “VINCENT HD and Night vision IR camera” used for the thermal imaging

• Noise (unwanted surrounding) Removal Using HSV Segmentation

The unwanted surroundings of the object are considered as noise. In the thermal video frames the living objects appear brighter as they emit greater infrared radiations than other. Hence HSV segmentation [29] is applied to remove the unwanted surroundings.

The image is converted to HSV color space form RGB color space as given below:

\[
\begin{align*}
1 + (G - B) / \Delta & \quad (\text{if } R = \max(R, G, B)) \\
3 + (B - R) / \Delta & \quad (\text{if } G = \max(R, G, B)) \\
5 + (R - G) / \Delta & \quad (\text{if } B = \max(R, G, B)) \\
S = [\max(R, G, B) - \min(R, G, B)] / \max(R, G, B) & \\
V = \max(R, G, B)
\end{align*}
\]

(1)

Where \( \Delta = [\max(R, G, B) - \min(R, G, B)] \) and \((R, G, B)\) is the RGB color space at pixel location \((x, y)\) in the image. At that point, the lower limit \(l_T\) and upper edge \(h_T\) range of the white color is characterized in HSV color space. The thresholding of the HSV color space is done to separate the white color in the image that addresses living objects.

\[
I_{Seg}(x, y) = \begin{cases} 
1 & (\text{if } l_T \leq I_{HSV}(x, y) \leq h_T) \\
0 & \text{else}
\end{cases}
\]

(2)

Where, ‘1’ and ‘0’ addresses white and black tones respectively, \(I_{HSV}(x,y)\) input image in HSV color space and \(I_{Seg}(x,y)\) is output image after noise removal. Finally, the objects are segmented and the surrounding objects is taken out in the output image.

• Deep Network for Object Recognition

Faster R-CNN [28] is utilized to recognize objects in the real time thermal images. The Region Proposal Network (RPN) utilizes ‘attention’ system to tell the Fast R-CNN [30] detector network where to look. In this work, VGG-16 network model [31] is utilized in Faster R-CNN model [28]. In default arrangement, there are anchors at position of image having 3 scales and 3 ratios. The anchors with an IOU more than 0.7 are classified as foreground and the anchors don't cover any ground truth object (IOU under 0.3) are classified as background. The loss function \(F_{Loss}\) to be limited is given as:

\[
F_{Loss}(m_v, n_v) = \frac{1}{C} \sum_{c} L_c(m_v, m^*_v) + \gamma \frac{1}{R} \sum_{r} m^*_v L_r(n_v, n^*_v)
\]

(3)

Where, \(m_v\) is the predicted anchor probability of anchor \(v\) being an object. Vector \(n_v\) signifies the parameterized coordinates of predicted bouncing box. \(L_r\) and \(L_c\) are the
regression and classification loss respectively. For classification, Cross Entropy Loss is utilized and for Bounding Box Regression smooth L1 loss is utilized. The normalization parameters $C$ and $R$ are mini batch size (i.e. $C=256$) and anchor locations (i.e. $R=2400$). The term $\gamma$ is the weight balancing parameter set to 10. The Fast R-CNN network utilizes cross entropy loss in between numerous object classes with end to end back propagation and Stochastic Gradient Descent with momentum having value of 0.9.

3. Result and discussion

For this work, VINCENT HD and Night vision IR camera is used to record the real time thermal video that has an approximate range of 1.5 km and resolution up to 720p but the video is recorded at a resolution of 360*450. The camera is set at channel number 101 assigned to night vision IR camera mode and IP address 192.168.1.65 is assigned to access camera remotely. The 749 frames are used evaluate the performance of proposed work as shown in Fig. 3. Faster R-CNN implementation is performed with configuration having Intel(R) Core(TM) i5-7200U CPU @ 2.50 GHz, 2701 MHz.

![Figure 3. Extracted frames from the video sequence captured by thermal Night vision IR camera.](image)

![Figure 4 (a). Input frame (b) Surrounding removal performed at threshold values $l_T=0.85$ and $h_T=1$.](image)

3.1 Object Recognition

HSV segmentation is used for the removal of the unwanted surroundings. As already discussed, living objects appear more white than other objects in thermal images because the living objects radiates more infrared rays than other objects. For the masking of white color space two thresholds ($l_T$ and $h_T$) are used. As the obstacles appear whiter than others, so the upper threshold $h_T$ is set to ‘1’ but the lower threshold $l_T$ is varied between 0.0-1.0 to get the optimum result. These results are recorded for HSV segmentation at threshold $l_T=0.85$, $h_T=1$ as shown in figure 4(b). Finally the Faster R-CNN network is applied to the output of the HSV segmentation to recognize objects in the thermal images. The performance of the network is revamped to enhance the accuracy by optimizing the parameter IoU threshold. The initial results of the proposed algorithm are obtained using threshold value 0.7 as shown in figure 5(c) but at the shorter distance from the camera. The lower IoU values provides better results in terms of timely identification but faced lower accuracy. The IoU threshold value ‘0.5’ is used which timely recognize the objects with good accuracy as shown in figure 5(g). The final results for the IoU=0.7 and 0.5 are shown in Fig. 5(d) and 5(h) respectively.
The proposed work performance is estimated with the help of parameters like accuracy, precision and recall. These parameters are evaluated for different values of the Intersection over Union (IoU) as shown in Table 1. The visual results and Table 1 concludes that the proposed system has better performance at IoU=0.5. Figure 6 illustrates the graphical comparison which also shows that the performance of this with accuracy of approximately 84.7%.

### Table 1. The proposed method performance for different IoU

| IoU | Accuracy | Precision | Recall  |
|-----|----------|-----------|---------|
| 0.5 | 0.847    | 0.851     | 0.873   |
| 0.7 | 0.818    | 0.799     | 0.832   |

4. **Conclusion and future scope**

The proposed strategy turns out sufficiently for the object recognition real time thermal images. This paper introduced a novel methodology dependent on deep learning network to distinguish objects in images caught utilizing thermal imaging framework. This work can be robust technique to build up an early warning framework to forestall mishaps for the public safety upgrade. This strategy will be likewise cost effective as it doesn’t need any huge change in the architecture as well as will decrease the monetary in terms of accidental compensation. The framework will be extended for recognition of other object classes near the vehicle to improve the framework.
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