Real Time Detection of Small Objects

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Abstract: The existing real time object detection algorithm is based on the deep neural network of convolution need to perform multilevel convolution and pooling operations on the entire image to extract a deep semantic characteristic of the image. The detection models perform better for large objects. However, these models do not detect small objects with low resolution and noise, because the features of existing models do not fully represent the essential features of small objects after repeated convolution operations. We have introduced a novel real time detection algorithm which employs upsampling and skip connection to extract multiscale features at different convolution levels in a learning task resulting a remarkable performance in detecting small objects. The detection precision of the model is shown to be higher and faster than that of the state-of-the-art models.

Keywords: Real time small object detection, small object classification, small object dataset pre-processing, segmentation of small object, deep learning for small object identification, image objects identification.

I. INTRODUCTION

Humans look at an image and instantly grasp what objects are within the image, wherever they are, and the way they act. The human sensory system is quick and accurate, allowing us to perform advanced tasks like driving with very little conscious thought. Fast, accurate, algorithms for object detection would enable computers to drive vehicles in any climate without specific sensors, empower assistive gadgets to pass on real-time scene data to human clients and unlock the potential of responsive robotic systems for general purposes [1,2,3,4].

Object detection is the process of finding real-world objects like faces, bicycles, buildings etc. from images or videos [5]. Current object detection algorithms such as You only look once (YOLO) [6,7], Single shot multibox detector (SSD) [8], Mask region-convolutional neural network (Mask RCNN) [9], Fast region-convolutional neural network (Fast RCNN) [10], Faster region-convolutional neural network (Faster RCNN) [11] and RetinaNet [12] repurpose classifiers [13,14] for detection. For the detection of an object these networks use classifiers for that object and evaluate it in a test image at different locations and scales. A sliding window approach is used by Systems like deformable parts models (DPM) [15,16] where the classifier runs across the entire image at evenly spaced locations.

The existing object detection literature focuses on detecting a large object that covers a large part of the image. The problem of finding a small piece of an image is largely overlooked [17,18]. The state-of -art algorithm for detecting small object offers unsatisfactory performance. The problem is the feature map which resolution become low because of convolution and the small object features get too small to be detectable. We’ve have worked to bridge the gap. To better evaluate the performance of small object detection, we first create a benchmark data set tailored to the problem of small object detection. Small object detection indicates detecting small objects which resolution are low and dominated by the environment. Small object detection has become very popular in the field of research because it can be helpful in satellite remote sensing, navigation, driving autonomous car and space observation.

In case of real time object detection, high rapidity is very important. And it is a big challenge for the researchers to maintain good accuracy with high rapidity in performance. We refer YOLOV3 (Figure 1) model because of its several benefits. The model was modified as per our demand and the modified model has more benefits over traditional models.

Fig. 1. The YOLO Detection System.

Important features of our algorithm are:
1. Feature resolution is made high by increasing the number of upsampling layers. Upsampling layers increase the lower resolution and the small objects do not lose its properties.
2. The speed of the model has been maintained 43 FPS using Nvidia GPU. This indicates that real time video streaming can be processed less than 20 milliseconds of latency.
3. The number of shortcut layers and the convolutional layers have been modified. The modified model was trained by increasing the number of shortcut and decreasing convolutional layers. It scored 0.972 training accuracy by training 130000 images.
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4. Small object dataset is not available. A huge dataset of 130000 images contained 20000 small object images was made. The model was trained through the dataset and maintained a good accuracy. All of our training and testing code has been uploaded to github. Even our pretrained model is available in there. At present we have kept the repository private because of paper review process.

II. RELATED WORKS

In the field of computer vision real time detection is a very hot topic. Some articles have spoken of max pooling and used it to implement image resolution. We’ve noticed that most of the model skips small objects when detected. So, it created an opportunity to do work on small object. Small object detection process, prepared by modifying from YOLOv3, carries out its prediction by generating boundary boxes on images. Classifier has been used by the model to define feature map. Furthermore, different types of classifier influence the accuracy of object detection. The classifier has been adjusted according to different types of detected objects to get good performance.

Hinton has used deep learning since 2012 to achieve the best possible classification accuracy in the ImageNet competition, and deep learning became a hot way of detecting objects. The object detection model is divided into two categories, based on deep learning: the first, widely used, is based on regional proposals [19,20] such as RCNN [9], SSP-Net [21], Fast-RCNN [10], Faster-RCNN [11] and R-FCN [22], respectively. The other approach does not use suggestions for regions but detects the objects directly, such as YOLO [6,7] and SSD [8].

The model selects Region of Interest (RoI) for the regional proposal method during first detection; i.e., selective search [23], edge box [24], or RPN [25] are used to produce multiple RoIs. The model then extracts features by CNN for each RoI, classifies objects by classifier and finally locates detected objects. RCNN [9] uses selective search [26] to generate around 2,000 RoIs for each picture and then extract and identify the 2000 RoIs convolution characteristics. Since these RoIs have many overlapping elements, the large number of repeated calculations contributes to inefficient detection. SSP-net [21] and Fast-RCNN [10] propose a specific RoI feature for this problem. The methods extract only one CNN function from the entire original image, and the RoI pooling operation extracts the feature of each RoI independently of the CNN function. Consequently, the calculation number for the extraction function of each RoI is shared. This method reduces the CNN operation needed 2000 times in RCNN to one operation in CNN that increases the computation speed considerably.

The other form does not have a proposed region for object detection. YOLO [6,7] breaks the entire original picture into the SxS grid. If the center of an object falls within a cell, the object is identified by the corresponding cell and the confidence score for each cell is set. The score represents the possibility of the target being in the boundary box and the precision of Intersection over Union (IoU). YOLO does not use region proposal but translates operations directly over the entire image, so speed is faster than Faster-RCNN, but the accuracy is lower than Faster-RCNN. SSD [8] also uses a single neural convolution network to transform the image, and predicts a series of boundary boxes of different sizes and length and width ratios for each point. During the test phase, the network predicts the probability of each object class in each boundary box and changes the boundary box to the shape of the object. G-CNN [26, 27] sees object detection as an issue moving the detection box from a fixed grid to an individual box. The model first divides the entire image into different scales to obtain the initial bounding box and extracts the characteristics from the entire image through the converting process. The feature image surrounded by an initial bounding box is then modified to a fixed size image by the Fast-RCNN method. Eventually, we can get a more accurate bounding box by regression process. After several iterations the final output will be the bounding box.

In short, there are two types of object detection methods for the current mainstream, the first one will be more accurate but the speed is slower. The accuracy of the second one is slightly worse, but faster. Regardless of the way the object is identified, the feature extraction uses multilayer convolution process, which can provide the rich abstract object functionality for the target object. But this approach leads to a reduction in detection accuracy for small target objects, since the features collected by the method are few and cannot fully represent the object’s characteristics.

III. THE MODEL

YOLOv3 is the third object detection algorithm within the YOLO (You Only Look Once) family. It is a feature learning-based network comprising 75 convolutional layers. There is no full-connection layer. That structure handles images of any size. There was no form of pooling. Stride is used for downsampling and moving the feature map. A ResNet-alike structure [28] and FPN-alike structure [29] are also a key to improving its accuracy. Figure 2 below provides full details of the YOLOv3 network.

![YOLOv3 Network Architecture](Image)

Fig. 2. YOLOv3 Network Architecture
The input images are used during training to predict 3D tensors which correspond to 3 scales (Figure 3). The three scales aim at detecting items of different sizes. If the ground truth bounding box in the middle of the object falls in a certain grid cell, this grid cell is responsible for determining the boundary box of the object. The corresponding object score is "1" for this grid cell and "0" for others. 3 preceding boxes of different sizes are assigned for each grid cell.

Fig. 3. YOLOv3 Process Flow
K-mean clustering is used to classify the total bboxes from dataset to 9 clusters before training. This results in 9 cluster sizes selected, 3 for 3 scales. This prior information is helpful for the network to learn to compute box offset/coordinate precisely because intuitively, bad choice of box size makes it harder and longer for the network to learn.

A. Modified Model Architecture

Fig. 4. Proposed Model Architecture
The figure 4 shows the architecture of the modified model. It consists of 60 convolutional layers, 20 skip connections and 6 upsampling layers. The number of convolutional layers has been decreased from 75 to 60 and upsampling layers have been increased from 2 to 6. It will help for better training. Besides the number of upsampling layers have settled to 20. Upsampling layers are being used for recreating image resolution. Due to convolution process the resolution of images go down. Upsampling layers recreate the resolution so that the information does not get losses and the objects do not remain untouched by the learning process of the model. Max pooling has not been used in here. Researchers argue that max pooling is responsible for information loss. It has kept unchanged because of getting better output. Conv 1x1 has kept unchanged as it does not make change to the size of image in output. The model perform prediction through bounding boxes.

B. Improvement of Anchor Box
The number of predefined bounding boxes have been increased. Our mission was to detect the small objects with big objects. So, we modified the height and width of bounding boxes and increased the number of boxes. Predefined bounding boxes are known as Anchor. Since we have five detectors per cell, we have five anchors. Small objects are therefore collected from detector 1, slightly larger objects from detector 2, long but flat objects from detector 3, tall but thin objects from detector 4, and large objects from detector 5.

C. Improvement of Scales for Detection
The model make prediction through 5 different scales (Figure 5). The detection layer is used to detect feature maps of five different sizes, each with steps 32, 16, 8, 4, 2. This means that we detect on scales 13 x 13, 26 x 26, 52 x 52, 104 x 104 and 208 x 208 with an input of 416 x 416. The network downsamples the input image to the first layer of detection where the feature maps of a stride 32 layer are used to detect it. Layers are upsampled by stride 2 and concatenated with feature maps of previous layers with the identical sizes of feature map. Another detection is currently created with stride 16 on the layers. The same upsampling procedure is repeated and a final detection is carried out at the stride 16, 8, 4 and 2 layers. Each cell predicts 5 bounding boxes with 5 anchors at each scale and the total number of anchors used is 25. Upsampling can help the network recreating the resolution so the network learns very well to both the small and big objects.

Fig. 5. Prediction through Different Scales
For an image size 416 x 416, the model predicts ((208 x 208) + (104 x 104) + (52 x 52) + (26 x 26) + (13 x 13)) x 5 bounding boxes.
It is huge in number. Thresholding has been used to minimize it. The values below a certain limit will be omitted.

D. Model Parameters

In the model $p_t$ is objectness score, $b_x$, $b_y$, $b_w$, $b_h$ are the center co-ordinate, $p_1$, $p_2$, $p_3$ are class confidence scores, box co-ordinates are $t_x$, $t_y$, $t_w$, $t_h$ and $p_w$, $p_h$ are anchor dimensions. The model uses Leaky Relu activation and predict through 5 anchor boxes. The model parameters have been listed in the table 1.

Table-I: Parameters Used in Model

| Name of Parameters | Symbol / values |
|--------------------|-----------------|
| Stride             | 32,16,8,4,2     |
| Number of anchor boxes | 5             |
| Filter             | 32,64,128,256   |
| Size               | 5               |
| Random             | 1               |
| Truth threshold    | 1               |
| Ignore threshold   | 0.7             |
| Jitter             | 0.3             |
| Num                | 9               |
| Classes            | 80              |
| Mask               | 0,1,2           |
| Route layers       | -4,-1,61        |
| Shortcut from      | -3              |
| Pad                | 1               |

IV. SIMULATION & RESULTS

YOLOV3 model was modified such a way that it can detect small objects from real time video or image. The modified model then trained by a dataset that was specially made for this model. As small object dataset is not available so a new dataset was prepared with images contains small objects. After the training process several test cases were done. The results have been described in next.

A. Dataset

A dataset was made to train the modified YOLOV3 model. Images were gathered from different sources. Approximately 130000 number of images contained 115 categories were collected. The images contained small and big objects which was used to train the model. Before training, the images were preprocessed. Rescaling, standardization, normalization, binarization were the steps for preprocessing. Gaussian distribution was used to standardize data and Gaussian blur used to remove noise from images. The configuration of our prepared dataset has been discussed in the table 2 and 3.

Table-II: Dataset configuration

| Number of Images | Properties                  |
|------------------|-----------------------------|
| Number of object Classes | 115                        |
| Training         | 112300                      |
| Validation       | 6055                        |
| Testing          | 10991                       |
| Regulation of Image (Average) | 469x387 pixels               |
| Per image object classes average | 1.221                    |

B. Hardware Configuration & Software used

We used machine that contained intel core i5 processor. 2 GB intel graphics memory + 2 GB NVidia GeForce 840m graphics memory. We used 240 GB SSD and 12 GB RAM. We used python 3.6, CUDA, Nvidia CUDA toolkit, pyTorch, OpenCV, TensorFlow, Matplotlib.

V. TRAINING & TESTING

The model used two steps training method. First, the model was trained and it generated a weight file. The weight file then used to obtain the final detection result. The weight file was generated through 8,000 iterations. Iteration indicates the number of passes using batch. One pass is the sum of one forward pass and one backward pass. As example we have 128000 training examples and batch size is 16. Then number of iterations will be 8000. The model scored 0.912 mAP at the time of training. And the test accuracy was maintained 0.829 (Figure 6).

A. Accuracy & Speed Comparison with Other Models

The paper compares the modified model to Faster-RCNN, Retina Net, YoloV2, YoloV3, SSD and R-FCN. The columnchat mentioned below will give information about the modified model and other related models in case of accuracy.
The modified model has scored higher accuracy than other yolo and related model (Table 4). The use of multi scaling feature, modified upsampling & shortcut layers, anchor boxes and convolution layers made the training much more accurate and that influenced the model to perform better than other models.

The modified model was designed such a way that it could prevent data or information loss. The model carries a lot of information because of using multi scaling and 5 predefined bounding boxes techniques. A huge number of information were needed to analyze by the model to prepare output. This made the model process little bit slower. The bar chart has compared the model with others in case of detection speed. The model still maintaining good speed which can detect small objects from a real-time video image. The model process 43 frame per second (Table 4) which indicates that output can be delivered within 23 milliseconds delay.

### B. Comparison of Mean Average Precision with Faster RCNN

In the model the loss has been decreased with the increasing number of iterations. Here we measured loss for 8 particular small objects for comparing loss with similar working model (Faster RCNN). We got accuracy 0.748 which has mentioned in details in Table 4. Our model scored loss 0.252 which is good enough than Faster RCNN.

Mean average precision is a metric for measuring the accuracy of object detectors. It is the mean average accuracy of various recall values. The accuracy scored by the model has been listed in Table 4.3. In here the accuracy has been compared with Faster RCNN. Faster RCNN has introduced small object detection multi scale feature. The model does not work in real time because of its low speed and poor accuracy.

#### Table-V: Mean Accuracy Precision our model vs Faster RCNN [11]

|                     | Faster RCNN | Modified Model |
|---------------------|-------------|----------------|
| mAP                 | 0.589       | 0.748          |
| Mouse               | 0.687       | 0.941          |
| Mobile              | 0.6         | 0.731          |
| Outlet              | 0.641       | 0.785          |
| Faucet              | 0.506       | 0.693          |
| Clock               | 0.585       | 0.712          |
| Toilet Paper        | 0.482       | 0.695          |
| Bottle              | 0.806       | 0.79           |
| Plate               | 0.402       | 0.635          |

#### C. Object Detection Comparison

Accuracy of the detection is stable when the number of YOLO network iterations is 8000 and the number of detection network iterations is 200000 from the above experiments. We are specially comparing with Faster-RCNN because it was used to detect small objects. The modified model is more accurate than others for all object types.

Remote sensing images are also detected in the real environment. The remote sensing image dataset comes from the Google map and UAV (unmanned aerial vehicle) [30, 31] photographs the field transmission line insulators. Because the images in the real environment have the characteristics of changing light, complex background and incomplete objects, we try to take into account all the special cases during the dataset construction. Experiments show that in real environments our proposed detection model has better results in detecting small objects. The object detection section renderings are shown in Figure 8.
In the figure 8 objects are being detected through the model from a real time video image. Small objects like the traffic, person, cars are being detected. The objects are far from the focus area and looking small but the model can recognize them.

VI. DISCUSSION & CONCLUSION

Small objects are very difficult to detect in real time, due to their lower resolution and greater influence on the environment. Existing detection models based on a deep neural network cannot detect small objects in real time because the properties of objects are extracted by multiple convolutions. Due to pooling activities information is lost. Our model not only retains the integrity of the function of the large object, but also preserves the full details of the small and large objects by extracting the multi-scale image, without using max pooling, skipping connections and upsampling layers. Thus, it can improve the accuracy of object detection. It provides high speed, allowing the detection of small and large objects in real time. In the modified model various scaling characteristics were used the picture is divided into so many grids the scale of which is very small. So, if a small object occurs then it must be identified. In addition to anchor box height and width also aid identification. The shallow layers learn quickly than the deep layers while studying profoundly. And the cycle of feeding deep layers is getting lower. The feeding cycle was improved with changed shortcut layers. So, the rate of learning has been rising. Layers of upsampling restore resolution when it becomes weak. Recreated resolution holds the small-object’s properties. So, through the modified model, the small object is being detected. The number of convolutional layers has been reduced so that pace does not decrease due to the enormous number of processes. Above all, the modified model detects small objects which maintain good precision and speed.

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