Public Transport Access Detection

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Abstract

We use a combination of You only look once object detection system and MobileNet architecture to perform object detection in order to help the visually impaired persons access the public transport system. Currently, the system detects cars, busses and license plates and it achieves around 20% mAP.

Classification

AMS Mathematical Subject Classification - 68T45 Machine vision and scene understanding

ACM Computing Reviews Categories and Subject Descriptors - I.4 IMAGE PROCESSING AND COMPUTER VISION - I.4.6. Segmentation - Edge and feature detection

1. Introduction

1.1 Context and motivation

According to the World Health Organization [9], the number of people suffering of some moderate to severe form of distance vision impairment or blindness due to cataract or uncorrected refractive error is around 200 million, out of the total of 2.2 billion people worldwide estimated to have some form of visual impairment. This represents a significant segment of the population that has troubles performing daily tasks. These troubles can be alleviated using assistive technologies (AT) that can help persons with disabilities maintain or enhance their capabilities.

Computers can extract and interpret meaningful information from digital images or videos using Computer Vision (CV), which is a multidisciplinary filed of artificial intelligence (AI) and deep learning (DL). It can be also regarded as a way of replicating the functions of the eye and the human visual cortex, or the area of the brain that processes visual information. So far, the functions of the eye are replicated, even exceeded, quite well by modern cameras. The functions of the visual cortex prove to be more difficult to replicate, but modern artificial intelligence models can perform well on specific tasks, sometimes rivaling the human image recognition capabilities.

Traditionally, running a complex enough deep learning model required so many resources that it could only run on large and expensive equipment. But, as technology advances, as predicted by Moore's law, powerful devices become more compact and are accessible to more people. Nowadays, phones have the needed hardware, such as integrated high resolution cameras and fast CPU's, to use artificial intelligence models to extract and interpret information about the surrounding environment. This means that computer vision can be integrated in daily activities.

Given the number of people that suffer of some form of visual impairment and the fact that computers can substitute visual functionalities, computer vision has the potential to play the main part of an assistive technology for the visually impaired persons (VIP), such that it helps the user to better understand the surrounding environment when performing different kinds of tasks. It is worth noting that this kind of technology can also prevent accidents. Also, a bonus is that anyone can have a phone, which is relatively cheaper and easier to use, compared to other specialized devices that might not even be available in all countries.

1.2 Objectives

One of the fundamental human needs is mobility and one important way of achieving it, is public transport. This way of travelling is especially important to the VIP since they are not allowed to drive. Therefore the main ways the VIP can travel is by public transport, ride-sharing or taxi, but they experience many difficulties on their journeys, often experiencing social exclusion because they are limited in their choices of public transport [8].

Therefore given that most mobility solutions don't provide adequate accessibility facilities, our aim is to develop a mobile assistive technology solution which provides spatial information through the use of real time object detection models. More specifically, the user can be guided towards bus or car by the auditory information provided by the mobile application. Furthermore, information about the location of the doors of the car or bus should be provided by using a feature detector with no trainable parameters. Also, information about the license plates should be provided to help the user to identify the vehicle.

1.3 Original contribution

The application aims to help the visually impaired persons by using computer vision and line detection, on a mobile device, to provide spatial information about public transport such as busses or ride sharing access. An object detector model will extract information about the vehicle and a line detector will analyze the part of the image containing the vehicle to extract information about the doors of the vehicle. This should eliminate the need for a dataset that has specific bounding box annotations for the doors.

1.4 Structure

In what follows, we describe in the second chapter the state of the art in object detection and the approach used in making public transport more accessible. In the third and fourth chapters, we describe our approach and some results.

2. Related work

Since the hardware became sufficiently advanced and accessible, the interest in object detection system increased, thus the need for a standardized dataset for comparing solutions appeared. Pascal VOC is one of the first datasets that proposes a variety of tasks such as object detection. It started as a challenge in 2007 [2] and it continued until 2012 [3]. Since then, mostly the combined datasets from 2007 and 2012 are used for training and validation and the test dataset from 2007 is used for testing and they are used as a common ground to compare performance across all kinds of computer vision tasks, such as object detection.

So far, the general idea in creating object detection datasets is to take an image and add bounding boxes around the objects of interest. But if we want to detect a specific feature of an object, for example if we want to detect the doors of a car, the current approach would be to take a dataset of images and add bounding boxes for the doors. This approach can take a long time and it requires further training of the model. Our approach should simplify this process, because we try to eliminate the need for additional bounding boxes and detect directly the required shapes. For example, if we need to detect bus doors we are looking for long vertical lines in the detected patch, that can be extracted by a line detector that eliminates the need for extra training. It is also expected that out approach is still real time, even though it adds and extra task and the accuracy shouldn't be affected.

2.1 Radio frequency approach

The current approach in making busses more accessible is a solution based on Radio Frequency Identification (RFID) [1]. Basically, it uses wireless radio frequency transmissions to transfer data between two devices. The systems is composed of four main parts: the device held by the VIP which is compatible with a braille keyboard, the bus station controller, a device on the bus and a database. The VIP searches the bus number and destination using his device. Then the bus controller sends signals to all busses in the radio frequency area, then passes back to the user the information about incoming busses, through a vocal message.

One disadvantage of this method is the complex infrastructure required.

Basically, the bus, station and the user are dependent upon each other. This makes it hard to implement it on a large scale and it does not guide the user towards the bus. Also, it requires expensive equipment for the user such as a braille keyboard, which is around 1000 dollars, a RFID reader which is around 100 dollars, and a personal digital assistant, which is around 20 dollars. The hardware needed for stations and busses is cheaper by a lot (around 1 dollar per bus or station), but it wouldn't be feasible because of the integration costs.

2.2 Computer Vision approach

Another approach would be to make the user independent of any infrastructure. This should give the user the freedom to access any bus, in any city, regardless if there are any accessibility features available or not. This can be achieved by using a mobile version of a computer vision model that tells the user where the bus is located by using real time object detection. This way there is no need for extra equipment.

We will focus especially on the single shot detector class of object detection models. Because their detection pipeline consists only of one neural network, they achieve real time speed with decent accuracy compared to other slower solutions.

2.2.1 You only look once

You only look once (YOLO) [10] is an object detection system that achieves real time performance. Before it, the task of object detection was decomposed in multiple tasks, that together make a pipeline, which is hard to train. For example, R-CNN [4] and it's faster variants first generate bounding boxes through selective search, then a convolutional network extracts features that are classified by a support vector machine. All of these steps slow down performance.

Instead of a long and complex detection pipeline, in YOLO, object detection is treated as a regression problem. There is only one neural network that predicts the bounding boxes and class probabilities from an image. This way, the network can be optimized end to end, and the inference time is greatly reduced, thus achieving real time performance.

The image is split into an SxS grid, each cell being responsible with the detection of one object. For each cell predicts B bounding boxes and for each box the position of the center, relative to the grid is predicted, the width and height are predicted relative to the image and a confidence score is predicted indicating if there is an object in that cell. Also, C class probabilities, conditioned on the cell containing an object, are predicted for each cell, regardless of the number of boxes B. Therefore, the network outputs a tensor of shape SxSx(B*5+C). In the second version of YOLO [11], the notion of anchors is introduced. This changes the output to be SxSxBx(5+C)), where B is the number of anchors. This allows the model to detect multiple objects in the same grid cell, with multiple shapes and sizes.

The network proposed by the authors is inspired by the GoogleLeNet model. It has 24 convolutional layers followed by 2 fully connected layers, although a faster version contains only 9 convolutional layers and fewer filters.

Leaky rectified linear activation function is on all layers, except the last one, where a linear activation function is used. Sum squared error is used for the loss function, but the authors note that it is not ideal because localization errors and classification errors are treated the same. Also, the cells that do not contain any images will have confidence scores close to zero, and can overcome the gradients from the cells that do contain objects, causing the training to diverge. To prevent this, two parameters that control the loss from bounding box coordinate predictions and the loss from confidence predictions are introduced. λ_{coord} increases the coordinate prediction loss and λ_{noobj} decreases confidence predictions loss.

For each cell, only one bounding box is chosen, the one with the highest input over union (IOU) with the ground truth. This causes the bounding box predictors to perform better on certain sizes, aspect ratios or classes, improving recall.

At test time, YOLO achieves great speeds because it only need a single pass through the network. Non-maximal suppression is used to choose between different bounding boxes.

Because each cell predicts only one object, multiple clustered small objects are harder to detect, thus the main source of error is localization error.

One important metric in measuring the performance of object detection systems is mean average precision (mAP). Precision measures the percentage of correct predictions for a given class. A prediction is considered true positive if the IOU is greater than a set threshold. Recall is another metric that measures the percentage of found positives. Both precision and recall depend on the given threshold for true positives. This means that by plotting different values for precision and recall for different thresholds we get a curve. The area under the curve is called average precision. And the mean over the area under the precision-recall curve for all classes is the mean average precision.

In terms of performance on the Pascal VOC 2007 dataset, first version of YOLO achieves 63.4% mAP and 45 frames per second (FPS), and the faster version has 52.7% mAP and 155 FPS. For comparison Faster R-CNN achieves 73.2% mAP but 7 FPS, which is accurate but very slow, and 100Hz Deformable parts model achieves 100 FPS but it has 16 mAP%. Therefore YOLO strikes a good balance between speed and accuracy.

2.2.2 Single Shot MultiBox Detector

Single shot MultiBox Detector (SSD) [7] is another example of object detection system that achieves real time performance, encapsulating all operations in a single deep neural network. Similar to YOLO, this helps SSD to outperform previous approaches that use multiple stages in detection such as R-CNN.

The network is composed of two parts. The first one consists of what is called the base network, which is a truncated version of a image classifier, where the classification layers are removed, that is used to extract features. On top of the base network several structures specific to object detection are added.

The key features of SSD are the multi-scale feature maps, convolutional predictors and default boxes.

At the end of the base network there are added convolutional feature layers that progresively decrease in size the feature map from the base network. This way predictions are made for each newly added layer, therefore, the predictions are made at various scales.

Each cell in each feature map has associated K default bounding boxes, whose positions are relative to their cell. Then for each box several kernels of size 3x3xP, where MxN is the size of the feature map and P is the number of channels, are used to predict C class probabilities and 4 offsets to the respective box. This means that each box uses $(C + 4) \cdot K$ filters, therefore the size of the predictions is $(C + 4) \cdot K \cdot M \cdot N$.

During training, the outputs need to be assigned to their corresponding ground truths. Then the loss function and back propagation are applied end-to-end. Furthermore, the set of default boxes and scales is chosen and hard negative mining and augmentation strategies are used.

For matching the outputs, each ground truth box is associated with the default box with the highest jaccard overlap. The novel approach here is that the default boxes are also matched with any ground truth box with jaccard overlap higher than a threshold. This allows predictions with high scores for multiple overlapping default boxes.

The loss is a weighted sum between confidence loss and localization loss.

Another crucial part is choosing scales and aspect ratios for the default boxes. Each feature map has a specific scale, distributed evenly between 2 values. The aspect ratios are chosen from a predefined set. The width and height are computed using the scale and the aspect ratio. The center is chosen based on the feature map cell size.

The matching steps produces more negatives than positives. This introduces an imbalance, and to fix this, the negatives are filtered by their confidence loss, so that a ratio of 3:1 is kept between the nagatives and positives.

Also, data augmentation is used. During training each for each images either a patch is randomly sampled, a path is sampled so that the minimum jaccard overlap with the objects is higher than a threshold, or the original image is used. After this, the image is resized and flipped with a probability of 0.5 and some photo-metric distortions are applied.

Regarding performance on the Pascal VOC 2007 dataset, SSD achieves 74.3% mAP and 59 FPS, surpassing the first version of YOLO in terms of accuracy and speed balance.

3. Design and implementation

The object detection part of the system is inspired from YOLOv2 [11]. We try 2 different model architectures for the model. Both are fully convolutional neural networks and use as backbone MobileNetv2 [13] because of it's flexibility and the fact that it uses depthwise convolutions, inverted residual blocks and linear bottlenecks, which all help with performance, thus consuming less power, which is crucial for mobile solutions. On top of the backbone a dropout layer is used for regularization to help prevent overfitting.

We use convolution blocks which are composed of a convolution layer that uses HeNormal initialization, a batch normalization layer and optionally a ReLU activation layer, and upsample blocks which are similar but use transposed convolution, which helps increase the spatial size of the input volume.

Both architectures add on top of the backbone a convolution block with 24 filters in our case, so that the final output is 13x13x3x8 after a reshape layer.

The second one is inspired from Unet [12]. It is called U because the shape of the model is like an U because features from earlier layers are added to the result through skip layers and upsample blocks. The chosen layers from MobileNet are: block_6_expand_relu, block_10_expand_relu and block_14_expand_relu. This helps the network to "see" the image at multiple resolutions as explained in the fine-grained features section in [11].

For training, we pretrain the MobileNet on ImageNet, then we use Adam optimizer and cosine annealing scheduler with $\eta_{min} = 1e-7$, $\eta_{max} = 4e-4$ and $T = 2 \cdot epochs$ for 5 epochs.

4. Experimental results

4.1 Dataset

For training the object detection system we use the Open Images Dataset V4 [6], available at [5]. In total, the dataset contains 9.2 million images, including 14.6 million bounding boxes across 600 classes on 1.74 million images. We will use only a subset of classes: bus, car and license plate.

The tool used to download the Bus, Car and License plate classes and the corresponding bounding boxes is OIDv4 ToolKit [14].

	Number of images	Number of bounding boxes			
		Total	Bus	Car	License plate
Train	30939	80295	11927	60516	7852
Validation	4967	9985	92	9381	512
Test	14894	30660	353	28737	1570

Table 4.1: Statistics related to the subset of Open Images

Each image is resized so that it's dimension is 416x416 and the bounding boxes are modified accordingly. This is done with the help of albumentations library in Python. The resizing helps the object detection task, as explained in [11], because this way we can split the image in a grid of 13x13 cells of size 32x32 so that there is a cell in the center that can detect the larger objects that are centered in the middle, rather than have 4 cells in the middle that try to detect the same object.

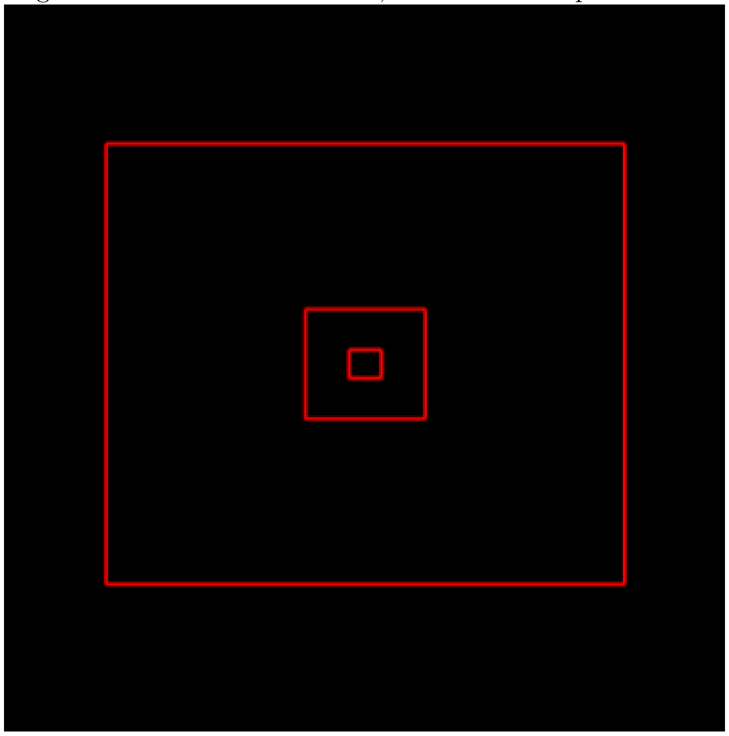
Each image is associated with multiple bounding boxes and each cell is responsible with detecting multiple bounding boxes through the use of anchors as explained in [11]. We use 3 anchors per cell so that each cell can detect various shapes and sizes. The anchor boxes are chosen using K-Means over the whole dataset.

For computing the distance between the centroid and bounding box the following formula is used, as in [11]:

$$distance(centroid, box) = 1 - IOU(centroid, box)$$

Where IOU represents intersection over union and is calculated as the area of the intersection of the 2 boxes over the area of union of the 2 boxes.

Figure 4.1: Anchors for the bus, car and license plate classes



This shows that the bounding boxes are roughly square.

Each image needs to be associated with a ground truth. We represent the ground truth as a CxCxBx8 tensor. For each cell in the CxC grid we associate B anchor boxes. Each anchor box has the following parameters: b_x and b_y represent the center of the box, b_w and b_h represent the width and height, c is the probability that the anchor predicts an object and c_1, c_2, c_3 represent the class probabilities. In our case C is 13 and B is 3.

The following formulas are used to compute the center, width and height from the output of the model:

$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w \cdot e^{t_w}$$
$$b_h = p_h \cdot e^{t_h}$$

Where t_x, t_y, t_w, t_h represent the raw predictions to which the sigmoid function is applied, c_x, c_y represents the coordinates of the upper left corner of the cell that predicts the box and p_w, p_h represent the width and height of the anchor that predicts the box.

After the bounding boxes are interpreted, usually Non-maximum Suppression (NMS) is used to filter the boxes with the best score and overlap with the ground truth and then mean average precision is used to see how good are the predictions.

4.2 Perfomance evaluation

To measure an object detection system performance, usually frames per second (FPS) and mean average precision (mAP) are used. Precision measures the percentage of correct predictions for a given class.

$$Precision = \frac{TP}{TP + FP}$$

A prediction is considered true positive if the IOU is greater than a set threshold. Recall is another metric that measures the percentage of found positives (also known as true positive rate).

$$Recall = \frac{TP}{TP + FN}$$

Both precision and recall depend on the given threshold for true positives. This means that by plotting different values for precision and recall for different thresholds we get a curve. The area under the curve is called average precision. And the mean over the area under the precision-recall curve for all classes is the mean average precision.

Over time, the mean average precision became the standard way of evaluating the performance of an object detection system in order to compare it with other solutions.

During training, the following sum-squared error loss function [10] is optimized to achieve better performance:

$$\lambda_{coord} \sum_{i=0}^{C^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2]$$

$$+\lambda_{coord} \sum_{i=0}^{C^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2]$$

$$+\sum_{i=0}^{C^2} \sum_{j=0}^{B} 1_{ij}^{obj} (C_i - \hat{C}_i)^2$$

$$+\lambda_{noobj} \sum_{i=0}^{C^2} \sum_{j=0}^{B} 1_{ij}^{noobj} (C_i - \hat{C}_i)^2$$

$$+\sum_{i=0}^{C^2} \sum_{j=0}^{B} 1_{ij}^{obj} \sum_{c \in classes} (p_{ij}^c log(\hat{p}_{ij}^c))^2$$

Most grid cells do not contain any boxes. Therefore in order to balance the confidence scores λ_{coord} and λ_{noobj} are added in order to increase the loss from bounding box predictions and decrease the loss from confidence predictions. Also, the square root of the width and height is used to remedy the problem that error in small and large boxes is weighted the same.

1_{ij}^{obj} is 1 for the j'th anchor box in the i'th cell if that anchor contains an object. 1_{ij}^{noobj} is 1 if 1_{ij}^{obj} is 0 for the given anchor and the IOU of the predicted box and any of the ground truth boxes exceeds a given threshold, otherwise it is 0.

We obtain with the simple model around 5% mAP and with the Unet inspired model around 20% mAP on the test set.

5. Conclusions and future work

We use a system along the lines of YOLO [10] to perform object detection on busses, cars, and license plates. For the feature extractor we use MobileNetV2 and for the object detection head we use 2 variants. A simple one with just one convolutional block which has poor performance and a Unet variant which is significantly better. Still, the results are poor compared to the current state of the art which is around 80% mAP depending on the speed/accuracy tradeoff and various parts can be improved such as the data preprocessing part, the hyperparameter fine tuning or the model architecture. Also, the postprocessing needs more improvement, currently this is the heaviest computationally part of the system. This would be critical in making the system real time.

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GitHub

The link to GitHub is the following: https://github.com/ComanacDragos/PublicTransportDetector.

And the link to the GitHub history is this https://github.com/ComanacDragos/PublicTransportDetector/commits/main.