A Saccaded Visual Transformer for General Object Spotting

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Abstract. This paper presents the novel combination of a visual transformer style patch classifier with saccaded local attention. A novel optimisation paradigm for training object models is also presented, rather than the optimisation function minimising class membership probability error the network is trained to estimate the normalised distance to the centroid of labeled objects. This approach builds a degree of translational invariance directly into the model and allows fast saccaded search with gradient ascent to find object centroids. The resulting saccaded visual transformer is demonstrated on human faces.

1 Introduction

The task of recognising or spotting general objects in images remains combinatorically difficult. The space of visual appearance of objects is both large and scales geometrically with the number of pixels in any image of an object to be recognised. Increasing the resolution of images of an object can make the computational aspects of object recognition harder.

Smaller distinguished sub-parts can be used to reduce the relevant search space for refined model matching. This style of recogniser is exemplified by finding SIFT[1] or MSER[2] etc. style features followed by geometric matching or bag of words indexing, reviews of discrete feature detectors include [3].

Convolution nets have represented the state of the art in object classification [4] but deeper networks like Resnet50 [5] offer a greater capacity to learn larger scale objects.

The Visual Transformer [6] offers a different approach using a higher dimensional model consisting of embedded feature vectors derived from learned basis functions for sub-patches covering an extended image patch. The size of the resulting network means large training sets are required (300M images to train 90M weights) and the networks are slow to apply. Adding new models to a network requires significant training resources. The degree to which the ViT demonstrates translational invariance is not clear.

This paper presents a novel optimisation paradigm for training transformer style object spotting/recognition networks that allows fast saccaded search. Visual transformers are typically trained through presenting vast numbers of larger
image patches that contain single exemplars of visual categories to the training system. The attraction of this being a single recogniser can be trained to distinguish thousands of visual categories at once. In the training process a set of basis functions are learned that allow the creation of a set of linear coefficients to represent the content of sub-patches and their relative locations. Visual inspection of the basis functions in the ViT paper [6] show them to bear at least a passing resemblance to visual receptive fields in higher animals [7].

This paper uses a similar network structure but seeks to create translation tolerant single object recognisers through the use of a novel optimisation criteria. Rather than training on error in probability of object class the system optimises predicted scaled distance from the labeled object centroid. Additionally sampling points may be drawn from a subset of image locations which are of high visual interest. In this paper the visual interest operator chosen is the ST-transform [8], returning the connected dark/light boundary chains as geometrically filterable candidate saccade points. Geometric filtering of the dark/light boundary could follow the ideas in [9] and [10].

The paper is laid out as follows: section 2 details the Distance to Feature based training function, the PyTorch network definition of the model being given in appendix A. Section 2.4 quantifies the speed benefits of only applying expensive classifiers at appropriate saccade points. Conclusions and directions for future research are given in section 3.

2 Distance to feature based training

In this paper we introduce distancetofeaturebasedtraining (DiFT) this involves sampling training patches from an image and assigning a target score based on the distance between the centre of the patch and the labeled centroid of a feature.

We use the Large-scale CelebFaces Attributes (CelebA) Dataset[11] as training data for our models. The dataset used contains rectified images where faces are scaled to a standard size in a 178x218 colour jpeg, this sets the scale for sample image patches and distance measures. We constructed training patches by taking a pair of random coordinates, which satisfy a minimum distance from the edge of the image (\( \left\lfloor \frac{x}{2} \right\rfloor \) for a patch of size \( x \)). Image patched can also be selected to be centered on candidate saccade points for an image.

2.1 Target score method

Let \((x_1, y_1)\) be the point at the centre of the training patch, and let \((x_2, y_2)\) be the point representing the feature. Then \( D_{12} \) is defined as the Euclidean distance between the two points.

\[
D_{12} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}
\]  

(1)

We then assign the training patch a target score between zero and one as a function of distance such that \( \text{score} = f(D) \); for the function \( f \) we used \( \frac{1}{2} \) as shown below.
\[ f(x) = \begin{cases} 
0 & x > 40 \\
\frac{1}{2} - \frac{x}{80} & 40 \geq x > 20 \\
1 - \frac{3x}{80} & 20 \geq x \geq 0
\end{cases} \] (2)

This piece-wise function decreases from 1 to 0.25 as \( x \) increases from 0 to 20, then decreases linearly to 0 as \( x \) increases to 40, with 0 gradient beyond \( x = 40 \). \( f \) is shown in [1] and in [2].

![Plot of the score function](image)

**Fig. 1.** Plot of the score function [2] on an 85 by 85 pixel grid. White represents a score of one, and black a score of zero.

In the case of an eye spotter image samples taken more than 40 pixels from a labeled eye are guaranteed to contain stuff that is not an eye.

This distance to feature method can easily be extended to multiple features by using a separate channel for each feature, as can be seen in [3] where one channel is used for eyes, another for nose tips and a third for mouth corners. This is how we trained a model on the landmarks from the CelebA dataset. The lower left image of [4] was produced by applying a convolutional neural network (CNN) [12] with a 35 by 35 pixel patch input trained as described above and then applied to the original image pixel-wise.

### 2.2 Benefits of distance to feature based training

The first benefit of distance to feature based training is that it can massively reduce the effort in creating training data. By assigning each pixel within a labeled image a score, each pixel effectively becomes a piece of training data, allowing one labeled image to become potentially thousands of training patches. This can reduce the amount of labeled training data needed and lower the impact of over-fitting models. Another benefit is that DiFT facilitated the use of gradient descent based methods to find feature centroids.
**Fig. 2.** A graph showing linearly decreasing score as distance increases until score is zero at forty pixels away from the feature.

**Fig. 3.** The score function applied to several features on a face. The red fields are centred on the centre of the eye, the green field on the tip of the nose and the blue fields on the mouth corners.
Fig. 4. Distance to feature based training applied to a CNN on a 35 by 35 patch. Red shows predicted distance from eyes, green for nose and blue for mouth corners. Top left is the input, top right is the output, bottom left is the output overlaid on the input, bottom right is the output with values below 0.5 set to 0, 0.5 – 0.8 set to 0.5 and above 0.8 set to 0.8.
2.3 Heatmaps and basis functions

Figure 5 shows the estimated distance to feature returned by the visualtransformer style CNN defined in ??.

As can be seen the most eye-like locations are centered on the eyes.

![Image](image.png)

**Fig. 5.** Image transformed by applying a CNN over a 31 by 31 pixel patch pixel-wise over the image.

Innate to the visualtransformer style of network is the linear embedding space which is effectively a set of learned convolution kernels. These learned convolution kernels arguably play a roll similar to receptive fields in the human visual system. While the ViT convolution kernels are not generally orthogonal they can be used as basis vectors in a weighted reconstruction of a sub-patch. From casual inspection the basis vectors perform poorly at reconstructing edge detail. This is perhaps a pointer to a limitation in the ability of the ViT to represent detailed shape.

A limited number of convolution kernels (basis vectors for feature embedding) was used in this paper largely because of limited training resources (one Mac mini M1 running PyTorch).
Fig. 6. The 16 by 16 convolution kernels of the CNN used in [5]
2.4 The role of Saccade in fast visual processing

Saccade is a quintessential part of the human visual system [13]. The human eye interrogates a scene via a series of rapid directed shifts (saccades) to point at feature points which provide an instantaneously stabilised retinal image. Even when the eye has alighted on a particular spot micro-saccades continue. Rather than uniformly scanning an image for objects to be recognised it is sufficient to focus on interest points. In this paper we choose to use the dark/light boundary chains returned by the ST transform [8] to provide a set of interest points. The length scale of the model together with the property that it returns an estimate of the distance to a model centroid means that only a fraction of the generalised feature points need to be sampled for object detection. Figure 7 shows the result of the ST-transform applied to a face image. The face image has 46,000 pixels giving dark/light boundary chains of 5,200 pixels which could be crudely sampled every 5 pixels to give 1,040 candidate search locations for objects of interest. Other geometry based boundary filters could be applied to give candidate saccade points.

Fig. 7. ST-transform applied to a face image, black pixels are dark/light region boundaries. There are significantly fewer boundary pixels than image pixels

3 Conclusions

Using the magnitude of distance from a sampled image patch to a labeled object centroid as the thing to be optimised in a Visual Transformer style network provides a classifier that is robust to translation with in the scale of the model. Using a generalised feature to provide candidate saccade points for image search vastly reduces processing time for visual search.
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To cite: [14], [15]

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A PyTorch Network Definition

PyTorch [16] was used as the NN training environment. A series of networks were evaluated with the one used to generate the results in this paper having the following definition within PyTorch.

class conv_face_features(nn.Module):
    def __init__(self, drop=0.):
        super().__init__()
        self.conv1 = nn.Conv2d(3,9,16)
        self.conv2 = nn.Conv2d(9,18,11)
        self.linear1 = nn.Linear(100,50)
        self.linear2 = nn.Linear(50*18, 256)
        self.linear3 = nn.Linear(256,64)
        self.linear4 = nn.Linear(64,16)
        self.linear5 = nn.Linear(16,3)
        self.act = nn.Mish()
        self.drop = nn.Dropout(p=drop)

    def forward(self,x):
        # x is torch.tensor(dtype=torch.float32) batch of patches [batchsize,3,height,width]
        x = x / 255.
        x = x.permute(0,3,1,2)
        x = self.conv1(x)

        x = self.drop(x)
        x = self.act(x)
        x = self.conv2(x)
        x = x.flatten(-2,-1)

        x = self.drop(x)
        x = self.act(x)
        x = self.linear1(x)
        x = x.flatten(-2,-1)

        x = self.drop(x)
        x = self.act(x)
        x = self.linear2(x)

        x = self.drop(x)
        x = self.act(x)
        x = self.linear3(x)

        x = self.drop(x)

x = self.drop(x)
x = self.act(x)
x = self.linear4(x)

x = self.drop(x)
x = self.act(x)
x = self.linear5(x)
return x

def training2(net, batches, batchsize, lr=0.05, momentum=0.9):
    net.train()
    criterion = nn.MSELoss() #MSE works, Cross-Entropy didn't work.
    optimizer = torch.optim.SGD(net.parameters(), lr=lr, momentum=momentum)
    running_loss = 0.
    for i in range(batches):
        d = specsfreeimage()
        inputs = torch.empty((batchsize, 31, 31, 3), dtype=torch.float32)
        scores = torch.empty(batchsize, dtype=torch.float32)
        for j in range(batchsize): #All patches in a batch are from same
            r = rand_coords(border=30)
            mindist = min_dist(d, r)
            scores[j] = score(mindist[0], 1)
            inputs[j] = torch.from_numpy(patch(d, r)).to(torch.float32)
        optimizer.zero_grad()
        outputs = net(inputs)
        loss = criterion(outputs, scores.unsqueeze(1))
        loss.backward()
        optimizer.step()
        running_loss += loss.item()
        print(i, ': ', str(running_loss/(i+1))[:7])