Convolutional STN for Weakly Supervised Object Localization and Beyond

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Abstract

Weakly-supervised object localization is a challenging task in which the object of interest should be localized while learning its appearance. State-of-the-art methods recycle the architecture of a standard CNN by using the activation maps of the last layer for localizing the object. While this approach is simple and works relatively well, object localization relies on different features than classification, thus, a specialized localization mechanism is required during training to improve performance. In this paper we propose a convolutional, multi-scale spatial localization network that provides accurate localization for the object of interest. Experimental results on CUB-200-2011 and ImageNet datasets show the improvements of our proposed approach w.r.t. state-of-the-art methods.

1. Introduction

Object localization is a key task in many computer vision applications such as autonomous driving [2], pedestrian detection [24], and earth vision [26]. In a standard learning setup, object localization requires full supervision, i.e., the class label and bounding box annotation for each object instance present in the image [4, 8, 9, 16, 17, 20, 18, 19]. However, obtaining bounding box annotations can be time consuming, in particular for large real-world image datasets. Moreover, human annotation can be subjective. Recently, several weakly supervised learning (WSL) techniques have been proposed for object localization, to alleviate the need for such expensive fine-grained annotations [29, 28, 22]. These techniques are applied in scenarios where supervision is either incomplete, inexact or ambiguous [31]. The inexact supervision scenario is often considered for object localization tasks, where training datasets only require global image-level annotations, i.e., the class label for each object in an image. For this reason, weakly supervised object localization (WSOL) techniques based on image-level annotations have gained much popularity in the computer vision community [1, 3, 7, 23, 30].

Deep convolutional neural networks (CNNs) with Class Activation Maps (CAM) [30] are a prominent solution in the literature for WSOL problems [22, 28, 30]. They use spatial class-specific localization maps where high activations indicate the location of the corresponding object of the class. CAMs are obtained through standard convolution, and as such, are limited in their ability to accommodate large and unknown transformations, and variations in object scale, orientation, and pose. Learning a transformation-invariant operation that can simultaneously handle different transformations is desirable for visual recognition systems. Spatial Transformer Networks (STNs) [12] have been proposed recently as a differentiable module that allows for spatial transformation of data within a CNN without manual intervention. This provides the network with flexibility in term of adaption to the input image variations. Since
the location of the activation in CAMs are intrinsically dependent to the convolution operation, flexible convolution operation that adapts to scale, orientation, and other possible variations are preferable. In this work, we investigate the use of STN [12] as an adaptive convolution operation to replace standard convolution. We refer to this operation as Convolutional STN (CSTN). This adaptation is achieved through the application of an STN convolution over each location. STN model learns affine transformations that can cover different variations including translation, scale, and rotation, allowing to better attend different object variations. This provides more flexibility compared to standard convolution. Figure 2 illustrates the difference between both types of convolution. In standard convolution, the sampling grid of the convolution is fixed (hence it has fixed receptive field) while in our CSTN, we transform the sampling grid using spatial transformers and sample the input feature map from the resulting locations allowing it to have a varying receptive field.

**Figure 2: An illustration of the difference between standard convolution and CSTN.**

While the CSTN is able to adapt to relatively small local variations, it still faces the issue of adapting to large variations in term of the receptive field. To alleviate this issue, we consider localizing objects of different scales at different levels (i.e., layers), using the Feature Pyramid Networks (FPN) [16]. The CSTN is applied at different levels of the feature pyramid. As the receptive field from the low layers can process only small regions of big objects, local convolution at that layer tend to localize small discriminative regions while missing the entire object. However, such layers are more adequate to localize small objects while high layers can miss them due to their large receptive field. To deal with this, an additional regularization term is introduced to drive specific layers to compete for the right scale. A joint probability over scale, location, and class is formulated based on the class scores through an aggregation process. Empirical study on popular weakly supervised benchmark datasets observed competitive performance on the localization task. Figure 1 illustrates how the CSTN is able to adapt to improve the localization. To summarize, our main contributions are, (1) a novel approach for WSOL with convolutional spatial transforms that explicitly learns to localize during classification. (2) an adaptation of the FPN model [16] to weakly supervised settings for localizing objects of different scale, where the STN need to learn a small transform for the right scale. (3) an empirical validation of the proposed approach over CUB-200-2011 bird dataset [25] and ILSVRC 2012 [21] localization dataset.

2. Related work

**Weakly supervised object localization:** The Class Activation Map (CAM) is a pioneering technique in WSOL was proposed by Zhou et al. [30]. It uses a simple and straightforward method to locate the strongly activated region using a fully convolutional classification network. Since it is primarily focused on achieving a high level of classification accuracy, its localization tends to correspond with the most discriminative object region. Most of the recent WSOL techniques propose updated versions of the CAM that can avoid the bias towards the discriminative region [22, 28, 29]. They typically seek to erase or hide the most discriminative region during training so that the classifier will focus on other relevant object regions. To achieve this, they leverage different strategies, like using multiple classifiers to localize complementary regions (ACoL) [28], self-produced guidance (SPG) [29], randomly hiding patches from the input image (HaS) [22].

**Deformable convolution:** The CSTN is in principle similar to deformable convolution proposed in [5]. To break the fixed geometry of a standard convolution, it learns a set of offsets for each position in the regular sampling grid. Deformable convolution has demonstrated improvements in object localization for the fully supervised object detectors [5, 27]. However the deformation learned in this way is not a centralized one as each pixel in the sampling grid can move independently resulting in irregular shape for the convolution. Active convolution unit proposed in [13] attempts to learn the shape of the convolution. All these deformable
convolution methods are studied in the fully supervised algorithms, we are the first to study it in a weakly supervised settings.

Spatial transformers: The Spatial Transformer Networks (STN) has been proposed by Jaderberg et al. [12] to learn a global affine transform of its input feature map. Driven by the classification objective, this global transform allows locating relevant object regions. This can be interpreted as a soft attention mechanism. Since it is a generic learnable module that can transform its input with respect to the network objective, it has found many application in, e.g., image captioning [14], disentangled representation learning [6] and image composting [15]. Our proposed method is applying it in a convolutional way to the weakly supervised localization problem. As in [12], the network objective of our CSTN is also to obtain accurate classification. However, the STN (global transform), the localization of objects on natural images cannot easily cope with the variations in the object scale. As described in the next section, by learning local transforms from the appropriate level, our CSTN is able to provide better localization than the global transform.

3. Overall Architecture

To explain our architecture for WSOL, we start from the last convolutional layer of a CNN and show how it is used for object localization (see Fig. 3(a)). Similar to one-stage object detection methods (e.g. SSD [17], YOLO [19]), we consider the location of a filter as the rough centre of the object. In one-stage detectors, this location is then associated with a set of class probabilities that defines which object is more likely to appear at that location and the coordinates of the object’s bounding box, estimated as a regression. In our case, we do not have information about the bounding box of the object as our problem is weakly supervised (we only have image-level label). Thus, to go from object labels to image labels we need an aggregation mechanism as detailed in the next subsection.

3.1. Joint class and location distribution:

In our model the last convolutional layer is a feature map $f$ with $H \times W = L$ locations and $C$ channels equivalent to the number of classes to classify. As shown in Fig. 3(b), we can consider this feature map as a voting for the most likely position and class in an image. We can thus convert this feature map into a multinomial probability distribution over classes and position by applying a softmax on the 2 spatial dimensions and on the channels too. As we want each class and location to compete, we need to compute a single softmax on the three dimensions. Thus, instead of the common distribution over classes $p(c)$, here we model the output of the CNN as a joint probability over classes and image locations.

$$p(c, l) = \frac{\exp(f_{c, l})}{\sum_{c'=1, l'=1}^{C, L} \exp(f_{c', l'})}. \quad (1)$$

With this joint probability distribution we can obtain the class labels by marginalizing over locations: $p(c) = \sum_l p(c, l)$. This can be used to train our model for classification with standard cross-entropy loss. However, with the joint probability, we can also obtain the maximum a posteriori (MAP) of the best location $l^*$ and class $c^*$ for a given image: $c^*, l^* = \arg \max_{c, l} p(c, l)$. This is the information required to estimate the location and class of the object of interest. This approach is simple and works well to find the centre of the object. However, we are interested in yielding
the bounding box of the object in the image. We can consider the bounding box of the object as proportional to the receptive field of the used feature map. However, this would lead to bounding boxes of the same scale. To overcome this problem in the next section we extend our approach to a multi-scale representation.

3.2. Multiscale search:

For searching at multiple scales we use feature pyramids [16], because it does not add much computational cost to the method and it works quite well on several problems. With the feature pyramid, instead of considering a single feature map \( f_{c,l} \), we use a representation composed by \( S \) feature maps, each representing the image at a different scale. Thus, we can extend our joint distribution to also scales: \( p(c, l, s) \) (see Fig. 3(c)). Again, by marginalizing over locations and scales we can obtain \( p(c) \) used for training, and by selecting the MAP, we can find the location \( i^* \) and \( s^* \) of the object of interest. Now, we can find objects at different scales and different locations. However, still, all objects will have the same aspect ratio. A possible solution would be to use convolutional filters of different sizes that will generate different receptive fields and therefore different bounding box shapes. However, this approach will increase the computational cost and will be able to provide only discrete object sizes (defined by the convolutional filters aspect ratio). In the next subsection we show how to learn a weakly supervised model that can adapt to any object size and aspect ratio.

3.3. Convolutional STN:

While in fully supervised object detection most of the approaches regress a bounding box with the right object size, for weakly supervised models it is difficult because there is not ground truth to regress. In the original spatial transformer network (STN), a localization network is trained to find global image transformations that can better represent the data and therefore minimize the training loss. The authors of the original paper show that this is an approach for improving the classification performance by focusing on the object of interest and at the same time, being able to localize the object of interest without annotations, thus in a weakly supervised manner. However, we note that STN works well when the data is quite clean (e.g., extended MNIST) and the sought transformations are relatively small. This is because the localization network of STN is trained with gradient descent, which is a local optimization. This means that when the transformation is too large or there is too much noise in the image, the local optimization will not be able to regress the correct transformation to localize the object and the training will fail. To overcome this problem, we propose to apply STN in a convolutional fashion. As shown in Fig. 3(d), for each feature map location we apply a localization network that reads the local features and generates a transformation based on those. As the STN is applied locally to each part of the image, the required transformation is smaller and it is more likely that the simple gradient based optimization used will work. Thus, in this work, the last layer is now composed of two stages: i) estimation of the local transformations \( \theta = \text{loc}(f) \), in which \( \text{loc} \) is a convolutional localization network that for each feature map location \( f_l \) returns a corresponding transformation \( \theta_l \). ii) the final representation \( f' = \text{conv}(f, \theta) \). The new layer is not much more expensive than a normal convolution because the additional computation is due only to the localization network. In contrast, being able to adapt the receptive field of the network to the local content of the image improves not only the localization of objects but also the image classification. Even though powerful, in the experimental evaluation we note that the convolutional spatial transformer tends quite easily to overfit the training data. To avoid that in the next subsection we present two regularization techniques.

3.4. Regularization:

Our multi-scale convolutional STN tends to focus on small regions. This is because during training, the selected bounding boxes shrink to the most discriminative part of an object while the classification performance improves. To address this, we added a regularization/penalty term to the classification loss which prevents the affine transformation \( \theta_1 \) from having large deviations from its reference location \( \theta_{ref} \). This regularization term is:

\[
L_{\theta} = \sum_{s \in S} \sum_{i=1}^{h_s \times w_s} ||\theta_{ref} - \theta_i||^2
\]

Here we choose \( \theta_{ref} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \) corresponding to the identity transform. The multi-scale search has also a bias towards localizing large objects from the lower levels of a feature pyramid. In order to make the higher levels compete for localizing large objects, we enforce the difference between the maximum activation of the two levels to be zero or negative, such that the higher feature map will be more likely to be selected. This can be applied on any two scale-adjacent feature maps \( s_1 \) and \( s_2 \).

\[
L_{scale}(x) = \max \left( 0, \max_{l} p(s = s_1, l, c = c^*|x) - \max_{l} p(s = s_2, l, c = c^*|x) \right)
\]

Note that for small objects which gets localized from the lower level, this doesn’t induce any penalty. Though the
Figure 4: **Overall System.** This figure illustrates how all the components of the system are used in order to train the model in a weakly supervised manner as well as to perform inference.

With these regularization terms, the final loss function optimized by our model is:

\[
L(x, y) = L_{cls}(x, y) + \lambda L_{\theta} + \alpha L_{scale}(x)
\]

where \(L_{cls}(x, y)\) is the multi-class cross-entropy loss, \(\alpha\) and \(\lambda\) are hyper-parameters to specify the strength of the STL and multi-scale regularizations.

3.5. Complete System

Fig.4 summarizes our complete system. Given an image, a feature pyramid network builds semantic representations of the image at different scales. On all the scales, a CSTN is applied so that for each location and scale a localization bounding box is estimated. Finally, the scores of the STN are converted into a joint probability \(p(c, l, s)\) over classes, locations, and scales. This can be converted to \(p(c)\) by marginalizing over scales and locations to obtain the class probabilities needed to train the model in a weakly supervised manner. During training, the proposed regularization is also used. The joint probability is used at test time to localize the object by a MAP inference.

4. Experiments

4.1. Experimental setup:

**Datasets and evaluation metric** We evaluated our multiscale convolutional STN model on CUB-200-2011 dataset \[25\] and ILSVRC 2012 \[21\] localization dataset. CUB-200-2011 contains 11,788 images of 200 bird species with 5,994 images for training and 5,794 for testing. ILSVRC 2012 dataset contains 1.28M training images and 50,000 validation images. There are 1000 categories of objects. For both datasets, we evaluate the performance in terms of classification and localization accuracy. An image is said to be correctly localized if the predicted class matches the true class and the predicted bounding box has 50% overlap with the ground-truth. The localization accuracy is denoted as Top-1 Loc in the results.

**Implementation details** We used ResNet101 \[10\] as the backbone network which is pre-trained on ImageNet \[21\] dataset. We removed the last average pooling and fully connected layer and added an additional convolution (with \(3 \times 3\) filter size and padding 1) and batch norm \[11\] layer. Feature pyramid is obtained from this network with its last two levels as described in \[16\]. The input images are resized to \(320 \times 320\) pixels. For data augmentation, we used horizontal flip with 50% probability. Images are normalized with mean = \([0.485, 0.456, 0.406]\) and std = \([0.229, 0.224, 0.225]\) as in ImageNet training \[21\]. The model is trained on NVIDIA GTX 1080 GPU with 12GB memory.

4.2. Ablation study:

The ablation studies are conducted to assess the impact of spatial transform, multi-scale localization and the regularization on \(\theta\). To assess the importance of the spatial transform, we computed the localization accuracy when the default box is used for localization instead of the transformed output from STN. Note that this doesn’t change the training procedure, since CSTN is still used the same way to learn the localization. At the implementation level, instead
of using the transformed coordinates, we used the original coordinates to compute the localization performance. Table 1 shows the result of this study on both the datasets. It can be observed that the transform is improving the localization around 5-8%. To see this impact visually, figure [5] shows some sample images where the transform is modifying the original receptive field box to improve the localization.

| Dataset          | Top-1 Loc without transform | Top-1 Loc with transform |
|------------------|----------------------------|--------------------------|
| CUB-200-2011     | 40.64                      | 49.03                    |
| ImageNet         | 36.69                      | 42.38                    |

Table 1: Impact of transform on the localization performance. For both dataset the convolutional spatial transformer is fundamental to obtain good performance.

To further study whether the CSTN is learning a good representation for localization we compared the localization performance with and without CSTN. For the case without CSTN, we used the same architecture and classification head, the only difference is that no transform is learned in this settings, i.e., instead of CSTN, a normal convolution is used. The classification head is now classifying the fixed sampling space of the convolution. Table 2 shows the result of this study on CUB-200-2011 dataset. It can be observed that without CSTN, the localization performance is reducing drastically. In contrast, for classification the impact of CSTN is reduced, but still present. This means that the CSTN not only learn to better localize an object in the image, but it also learn a better representation of the object that produces an improved classification.

| Type             | Top-1 Class | Top-1 Loc |
|------------------|-------------|-----------|
| Without conv STN | 77.40       | 21.64     |
| With conv STN    | 78.46       | 49.03     |

Table 2: Localizing with and without convolutional STN on CUB-200-2011 dataset. It can be observed that the convolutional STN is very effective in learning a good representation for localization. It improves the localization by 26.79%.

The multi-scale localization is another important component in our model. To assess the importance of this, we conduct ablation experiments with localization from two level of the feature pyramid independently and compare it with the model where these levels are combined. Figure [6] shows the results from this study. Here the histogram is created by dividing the area of the bounding box into 10 bins of equal size. The histogram shows in green the total number of samples at each resolution and in blue and red the percentage of images that are correctly localized in each bin for the model without and with bounding box transformations. From the figure (a) and (b) we see that different levels are specialized on different object sizes. With the multi-scale model (c) we balance the localization between the two levels and improve the localization accuracy. Note also that the effect of the bounding box transformation become stronger when using a multi-scale model. This is in line with out hypothesis that the STN performs a local optimization and for improved performance, the transformations should be relatively small. Adding multiple scales reduces the gap between the estimated position of an object and its real position (because we have bounding boxes at multiple scales). This facilitates the search of the spatial transformer and therefore leads to improved performance.

Another important component of our method is the regularization on $\theta$. We observed that without this regularization, the learned transformations are not from the distribution of possible object bounding boxes. The transform tends to overfit and shrink to discriminative image parts resulting in poor localization. Figure [7] show samples of bounding boxes learned without using regularization on $\theta$. To obtain a good localization, tuning the hyperparameter $\lambda$ is critical. Table 3 shows the performance in classification and localization for different values of $\lambda$. As expected, while the model classification is barely affected, localization is highly affected by this parameter. For the regularization on the scales, we found that $\alpha$ can vary in a range of values without affecting too much the localization results. Thus we did not include a study on that.

| $\lambda$ | Top-1 Loc | Top-1 Class |
|-----------|-----------|-------------|
| 0.01      | 27.39     | 78.98       |
| 0.001     | 30.88     | 78.63       |
| 0.0001    | 49.03     | 78.46       |
| 0.00001   | 45.52     | 78.25       |
| 0         | 5.13      | 77.32       |

Table 3: Impact of $\lambda$ on classification and localization accuracy. For a high value of $\lambda$ the localization accuracy tends to the one obtained without STN. For no regularization, the transformations become too strong and focus on small parts of the object thus producing a very poor localization score.

### 4.3. Comparison with state-of-the-art methods:

We compare the localization of the CSTN with state-of-the-art solutions for WSOL. The results are summarized in table [4] and table [5] for CUB-200-2011 and ILSVRC 2012 respectively.

On the CUB-200-2011 dataset, CSTN performs better than all the CAM based methods. In this dataset, the scale of objects are distributed unevenly, i.e., many objects are of nearly the same size, extreme variations in the size are
very less (not too many small and large objects). As we have seen, different levels of the CSTN specializes on different scales, we can get the best of the localization from this model by focusing more on the crowded scales (where there are many objects). The hyperparameter $\lambda$ is not very sensitive to the Top-1 Loc in this case, so it can be tuned fairly easily.

On the ILSVRC dataset CSTN is outperformed by many of the CAM based method. This is probably due to the sensitivity to the scale. The number of objects in different scales are nearly uniformly distributed in this dataset. So the multi-scale localization should specialize on each scale equally well in this case. This can be better explained with the histogram of localization on ImageNet shown in figure 8. As we can see, it favours the localization towards large objects in this case. As a result, it fails to localize most of the smaller objects. We should probably test the method with a higher resolution input image in order to better localize small objects.

Also, we believe that improving the multi-scale localization component of our method can close this performance gap compared to the state-of-the-art CAM based WSOL. The softmax aggregation strategy is a simple and straightforward expansion to introduce the multi-scale capability. Having better methods to select the matching scale can bring the benefit of CSTN to all such multi-scale improvements. Also, an improvement in classification accuracy can also boost the localization further. Without checking the correctness in the class prediction, our method can localize up to 57.02% images in the validation set.

If we try to localize an object with the wrong scale (ie, from the wrong level of the feature pyramid), it will end-up in getting stuck at some discriminative object region. Figure 9 shows some failure cases of this when localizing large objects using CSTN. Since the end goal of STN is still to get a good classification, it will not try to localize the integral object.
5. Conclusion

In this work we have introduced a novel method for weakly supervised object localization. Instead of using the classical Class Activation Maps, we show that the use of a convolutional spatial transformer can lead to high performance by regressing the object bounding box, similarly as in fully supervised object detection approaches. This approach can be plugged into any convolutional network giving an end-to-end weakly supervised localization module. The learning of the convolutional STN if fairly easy and it adds few additional convolutional layers to the standard CNN. Our Convolutional STN with multi-scale localization gives competitive results on the benchmarked datasets. Empirical study reveals that the localization with convolutional STN is sensitive to the object scale and we have proposed two regularization strategies to deal with those issues. Future work is about extending the method to weakly supervised object detection.
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