Generic Object Detection with Dense Neural Patterns and Regionlets

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Abstract

This paper addresses the challenge of establlishing a bridge between deep convolutional neural networks and conventional object detection frameworks for accurate and efficient generic object detection. We introduce *Dense Neural Patterns*, short for DNPs, which are dense local features derived from discriminatively trained deep convolutional neural networks. DNPs can be easily plugged into conventional detection frameworks in the same way as other dense local features(like HOG or LBP). The effectiveness of the proposed approach is demonstrated with *Regionlets* object detection framework. It achieved 46.1% mean average precision on the PASCAL VOC 2007 dataset, and 44.1% on the PASCAL VOC 2010 dataset, which dramatically improves the original *Regionlets* approach without DNPs.

1. Introduction

Detecting generic objects in high-resolution images is one of the most valuable pattern recognition tasks, useful for large-scale image labeling, scene understanding, action recognition, self-driving vehicles and robotics. At the same time, accurate detection is a highly challenging task due to cluttered backgrounds, occlusions, and perspective changes. Predominant approaches (Felzenszwalb et al., 2010) use deformable template matching with hand-designed features. However, these methods are not flexible when dealing with variable aspect ratios. Wang *et al.* recently proposed a radically different approach, named *Regionlets*, for generic object detection (Wang et al., 2013). It extends classic cascaded boosting classifiers (Viola & Jones, 2001) with a two-layer feature extraction hierarchy which is dedicatedly designed for region based object detection. The innovative framework is capable of dealing with variable aspect ratios, flexible feature sets, and improves upon Deformable Part-based Model by 8% (Wang et al., 2013). Despite the success of these sophisticated detection methods, the features employed in these frameworks are still traditional features based on low-level cues such as histogram of oriented gradients(HOG) (Dalal & Triggs, 2005), local binary patterns(LBP) (Ahonen et al., 2006) or covariance (Tuzel et al., 2008) built on image gradients.

As with the success in large scale image classification (Krizhevsky et al., 2012), object detection using a deep convolutional neural network also shows promising performance (Girshick et al., 2013; Sermanet et al., 2013). The dramatic improvements from the application of deep neural networks are believed to be attributable to their capability to learn hierarchically more complex features from large data-sets. Despite their excellent performance, the application of deep CNNs has been centered around image classification, which is computationally expensive when transfering to object detection. For example, the approach in (Girshick et al., 2013) needs around 2 minutes to evaluate one image. Furthermore, their formulation of the problem does not take advantage of venerable and successful object detection frameworks such as DPM or *Regionlets* which are powerful designs for modeling object deformation, sub-categories and multiple aspect ratios.

These observations motivate us to propose an approach to efficently incorporate a deep neural network into conven-

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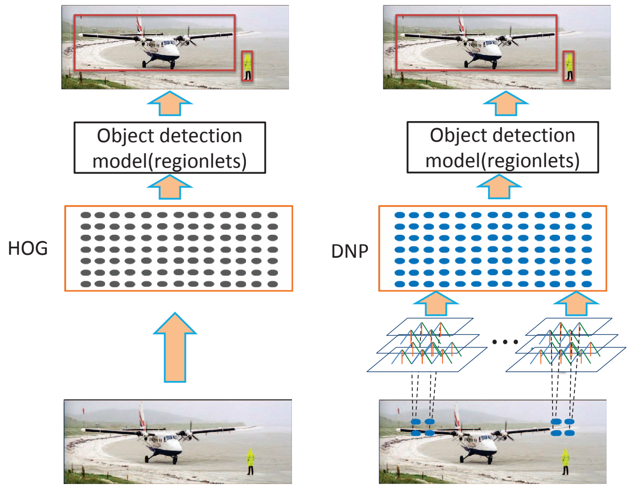


Figure 1. Deep Neural Patterns (DNP) for object detection

tional object detection framework. To that end, we introduce *Dense Neural Pattern* (DNP), a local feature densely extracted from an image with arbitrary resolution using a well trained deep convolutional neural networks. The DNPs not only encode high-level features learned from a large image data-set, but are also local and flexible like other dense local features (like HOG or LBP). It is easy to integrate DNPs into the conventional detection frameworks. As shown in Figure 3 and Figure 4, we illustrate the DNPs extraction process using the fifth convolutional layer of the network we trained. The fifth convolutional layer consists of 256 feature maps, each of which has 13×13 convolutional output. Each output corresponds to a local receptive field (Hubel & Wiesel, 1968) in the input image. The center of the receptive field can be back-tracked through the convolutional and pooling layers. It is shown that, when mapping all the fifth layer convolution output back to the input image, we obtain 169 (13×13) feature vectors (DNPs) for 169 locations with stride of 16 pixels[1]. Dense features for the whole image is easily obtained by shifting the convolution window of the neural network, or "*network convolution*"[2]. As the result, a typical PASCAL VOC image only needs to run the neural network several times to produce DNPs for the whole image depending on the required feature stride, promising low computational cost for feature extraction. To adapt our features for the *Regionlets* framework, we build normalized histograms of DNPs inside each sub-region of arbitrary resolution within the detection window and add these histograms to the feature pool for the boosting learning process. DNPs can also be easily combined with traditional features in the *Regionlets* framework as explained in Sec. 3.3.

[1]The usable feature points are less due to padding effects which is explained in Sec. 3.2.

[2]To obtain DNPs with smaller strides, for example 8 pixels, we can shift the image by 8 pixels to extract a new set of DNPs and added them to the original set.

Our experiments show that the proposed DNPs are very effective and also complementary to traditional features. On PASCAL 2007 VOC detection benchmark, our framework with *Regionlets* and DNPs achieved 46.1% mAP compared to 41.7% with the original *Regionlets*; on PASCAL VOC 2010, it achieves 44.1% mAP compared to 39.7% with the original *Regionlets*. It outperforms the recent approach by (Girshick et al., 2013) with 43.5% mAP. Furthermore, our DNP features are extracted from the fifth convolutional layer of the deep CNN without fine-tuning on the target data-set, while (Girshick et al., 2013) used the seventh full connected layer with fine-tuning. Importantly, for each PASCAL image, our feature extraction finishes in 2 seconds, compared to approximately 2 minutes from our replication of (Girshick et al., 2013).

The major contribution of the paper is two-fold: 1) We propose a method to incorporate a discriminatively-trained deep neural network into a generic object detection framework. This approach is very effective and efficient. 2) We apply the proposed method to the *Regionlets* object detection framework and achieved competitive and state-of-the-art performance on the PASCAL VOC datasets.

2. Review of Related Work

Generic object detection has been improved over years, due to better deformation modeling, more effective multi-viewpoints handling, occlusion handling. Complete survey of the object detection literature is certainly beyond the scope of this paper. Representative works include but not limited to Histogram of Oriented Gradients (Dalal & Triggs, 2005), Deformable Part-based Model and its extensions (Felzenszwalb et al., 2010), *Regionlets* (Wang et al., 2013), *etc*. This paper aims at incorporating discriminative power of a learned deep CNN into these successful object detection frameworks. The execution of the idea is based on *Regionlets* object detection framework which is currently the state-of-the-art detection approach without using a deep neural network. More details about *Regionlets* are introduced in 3.3.

More discriminative and robust features are always desirable in object detection, which are arguably one of the most important domain knowledge developed in computer vision community in past years. Most of these features are based on colors (Shahbaz Khan et al., 2012), gradients (Dalal & Triggs, 2005), textures (Ahonen et al., 2006; Wang et al., 2009) or relative high order information such as covariance (Tuzel et al., 2008). These features are generic and have been demonstrated to be very effective in object detection. However, none of them encodes high-level or even semantic information. The DNPs proposed in this paper complement existing features in this aspect. Their combination produces much better performance than applying either one individually.

Recently, deep learning with CNN has achieved appealing results on image classification (Krizhevsky et al., 2012). This impressive result is built on prior work on feature learning (LeCun et al., 1998; Hinton et al., 2012). The availability of large datasets like ImageNet (Deng et al., 2010) and high computational power with GPUs has empowered CNNs to learn deep discriminative features. A parallel work of deep learning (Le et al., 2012) without using convolution also produced very strong results on the ImageNet classification task. In our approach, we choose the deep CNN architecture due to its unique advantages related to an object detection task as discussed in Sec. 3.1. The most related work to ours is (Girshick et al., 2013) which converts the problem of object detection into region-based image classification using a deep convolutional neural network. Our approach differs in two aspects: 1) We provide a framework to leverage both the discriminative power of a deep CNN and recently developed effective detection models. 2) Our method is 74x faster than (Girshick et al., 2013). There have been earlier work in applying deep learning to object detection (LeCun et al., 2004; Le et al., 2011). Among these, most related to ours is the application of unsupervised multi-stage feature learning for object detection (Sermanet et al., 2012). In contrast to their focus on unsupervised pre-training, our work takes advantage of a large-scale supervised image classification model to improve object detection frameworks. The deep CNN is trained using image labels on an image classification task. Learning deep CNN in an unsupervised manner for our framework may also be interesting but not the current focus of the paper.

The proposed approach is a new example of transfer learning, *i.e*. transferring the knowledge learned from large-scale image classification (in this case, ImageNet image classification) to generic object detection. There have been some very interesting approaches in transferring the learned knowledge by deep neural networks. For example, (Raina et al., 2007) and (Pan & Yang, 2010) illustrated transfer learning with unlabeled data or labels from other tasks. Our work shares a similar spirit but in a different context. It transfers the knowledge learned from a classification task to object detection by trickling high-level information in top convolutional layers in a deep CNN down to low-level image patches.

3. Dense Neural Patterns for Object Detection

In this section, we first introduce the neural network used to extract dense neural patterns, Then we provide detailed description of our dense feature extraction approach. Finally, we illustrate the techniques to integrate DNP with the *Regionlets* object detection framework.

3.1. The Deep Convolutional Neural Network for Dense Neural Patterns

Deep neural networks offer a class of hierarchical models to learn features directly from image pixels. Among these models, deep convolutional neural networks (CNN) are constructed assuming locality of spatial dependencies and stationarity of statistics in natural images (LeCun & Bengio, 1995; Krizhevsky et al., 2012; Ranzato & LeCun, 2007). The architecture of CNNs gives rise to several unique properties desirable for object detection. Firstly, each neuron in a deep CNN corresponds to a receptive field (Hubel & Wiesel, 1968) whose projected location in the image can be uniquely identified. Thus, the deeper convolutional layers implicitly capture spatial information, which is essential for modeling object part configurations. Secondly, the feature extraction in a deep CNN is performed in a homogeneous way for receptive fields at different locations due to convolutional weight-tying. More specifically, different receptive fields with the same visual appearance produce the same activations. This is similar to a HOG feature extractor, which produces the same histograms for image patches with the same appearance. Other architectures such as local receptive field networks with untied weights (Le et al., 2012) or fully-connected networks [3] do not have these properties. Not only are these properties valid for a one-layer CNN, they are also valid for a deep CNN with many stacked layers and all dimensions of its feature maps[4]. By virtue of these desirable properties, we employ the deep CNN architecture. We build a CNN with five convolutional layers interweaved with max-pooling and contrast normalization layers as illustrated in Figure 2. In contrast with (Krizhevsky et al., 2012), we did not separate the network into two columns, and our network has slightly larger number of parameters. The deep CNN is trained on large-scale image classification with data from ILSVRC 2010. To train the neural network, we adopt stochastic gradient descent with momentum (LeCun et al., 1998) as the optimization technique, combined with early stopping (Girosi et al., 1995). To regularize the model, we found it useful to apply data augmentation and the dropout technique (Hinton et al., 2012; Krizhevsky et al., 2012). Although the neural network we trained has full connected layers, we extract DNPs only from convolutional layers since they preserve spatial infor-

[3] Neural networks in which every neurons in the next layer are connected with every neuron on the previous layer

[4] To see this in an intuitive sense, one could apply a "*network-convolution*", and abstract the stack of locally connected layers as one layer

mation from the input image.

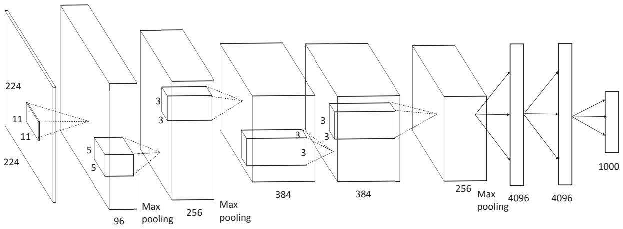


Figure 2. Architecture of the deep convolutional neural network for extracting dense neural patterns.

3.2. Dense Neural Patterns

After the deep CNN is sufficiently trained on large-scale image classification, this recognition module is employed to produce dense feature maps on high-resolution detection images. We call the combination of this technique and the resulting feature set Dense Neural Patterns (DNPs).

The main idea for extracting dense neural pattern is illustrated in Figure 3 and Figure 4. In the following paragraphs, we first describe the methodologies to extract features using a deep CNN on a single image patch. Then, we describe the geometries involved in applying "*network-convolution*" to generate dense neural patterns for the entire high-resolution image.

Each sub-slice of a deep CNN for visual recognition is commonly composed of a convolutional weight layer, a possible pooling layer, and a possible contrast-normalization layer (Jarrett et al., 2009). All three layers could be implemented by convolutional operations. Therefore, seen from the perspective of preserving the spatial feature locations, the combination of these layers could be perceived as one convolutional layer with one abstracted kernel. The spatial location of the output can be traced back by the center point of the convolution kernel.

As shown in Figure 3(b), each convolution kernel produces a sheet of neural patterns. To tailor dense neural patterns into a flexible feature set for object detectors, we compute the 2-D location of each neural pattern and map it back to coordinates on the original image. As an example, we show how to compute the location of the top-left neural pattern in Figure 3(b). The horizontal location x of this top-left neural pattern feature is computed with Equation 1:

$$x_i = x_{i-1} + (\frac{W_i - 1}{2} - P_i)S_{i-1} \tag{1}$$

where $i > 1$, $x_1 = \frac{W_1 - 1}{2}$, x_{i-1} is the top-left location of the previous layer, W_i is the window size of a convolutional or pooling layer, P_i is the padding of the current layer, S_{i-1} is the actual pixel stride of two adjacent neural patterns output by the previous layer which can be computed with Equation 2

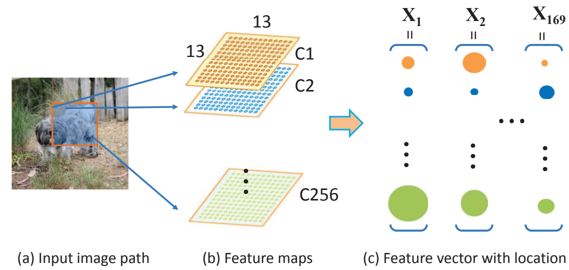


Figure 3. Neural patterns extraction with location association. (a) A square region (224×224) as the input for the deep neural network. (b) Feature maps generated by filters in the fifth convolution layer, spatially organized according to their inherited 2-D locations. Each map has 13×13 neural patterns. (c) Feature vector generated for each feature point. A bigger circle indicates a larger neural activation.

$$S_i = S_{i-1} \times s_i. \tag{2}$$

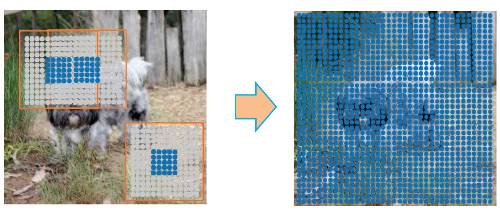
Here s_i is the current stride using neural patterns output by previous layers as "pixels". Given equation 1 and equation 2, the pixel locations of neural patterns in different layers can be computed recursively going up the hierarchy. Table 1 shows a range of geometric parameters, including original pixel x coordinates of the top-left neural pattern and the pixel stride at each layer. Since convolutions are homogeneous in x and y directions, the y coordinates can be computed in a similar manner. Coordinates of the remaining neural patterns can be easily computed by adding a multiple of the stride to the coordinates of the top-left feature point. To obtain a feature vector for a specific spatial location (x, y), we concatenate neural patterns located at (x, y) from all maps(neurons) as illustrated in Figure 3(c).

Table 1. Compute the actual location x_i of the top-left neural pattern and the actual pixel distance S_i between two adjacent neural patterns output by layer i, based on our deep CNN structure.

i	Layer	W_i	s_i	P_i	S_i	x_i
1	conv1	11	4	1	4	6
2	pool1	3	2	0	8	10
3	conv2	5	1	2	8	10
4	pool2	3	2	0	16	18
5	conv3	3	1	1	16	18
6	conv4	3	1	1	16	18
7	conv5	3	1	1	16	18
8	pool3	3	2	0	32	34

Now that a feature vectors can be computed and localized, dense neural patterns can be obtained by "*network-convolution*". This process is shown in Figure 4. Producing dense neural patterns to a high-resolution image could be trivial by shifting the deep CNN model with 224×224 input over the larger image. However, deeper convolutional networks are usually geometrically constrained. For instance, they require extra padding to ensure the map sizes and borders work with strides and pooling of the next layer. Therefore, the activation of a neuron on the fifth convolutional layer may have been calculated on zero padded values. This creates the inhomogeneous problem among neural patterns, implying that the same image patch may produce different activations. Although this might cause tolerable inaccuracies for image classification, the problem could be detrimental to object detectors, which is evaluated by localization accuracy. To rectify this concern, we only retain central 5×5 feature points of the feature map square. In this manner, each model convolution generates 25 feature vectors with a 16×16 pixel stride. In order to produce the dense neural patterns map for the whole image using the fifth convolutional layer, we convolve the deep CNN model every 80 pixels in both x and y direction. Given a 640×480 image, it outputs 40×30 feature points which involves 8×6 model convolutions.

The DNP feature representation has some desirable characteristics which make it substantially different from and complementary to traditional features used in object detection.



(a) Convolution with a stride of $m \times 16$ pixels

(b) Output the dense neural patterns

Figure 4. Dense feature maps obtained by shifting the classification window and extract neural patterns at center positions.

Robustness to boundary effects caused by local shifts Most hand-crafted features, are not robust to local shifts due to the hard voting process. Given HOG for example, gradient orientations are hard voted to spatial(8×8) histograms. Features close to the boundary of two feature regions may be in one region on one example, but the other on another example which causes substantial feature representation change. The boundary effects may cause difficulties in robustness detection. Moreover, if we shift the window by 8 pixels, extracted features are completely misaligned. On the contrary, the max-pooling in DNPs explicitly handles reasonable pixel shifts. The dense convolution with shared weights, the data driven learned invariance also implicitly further improve the robustness to boundary effects and local shifts.

Local features with high-level information Another significant advantage of DNPs is that the hierarchical architecture of CNNs offers high-level visual features. More specifically, the features are indicative of object-level or object-part level visual input. To validate this, we find the image patches that causes large responses to a selected neural pattern dimension in the deep layers of the CNN. This visualization is shown in Figure 8. It suggests that patches which have large feature responses to the same neural pattern dimension correspond to similar object category, color or contour. In this respect, DNPs offers significant advantages over traditional features for object detection. Details about the visualization can be found in Sec. 4.2.

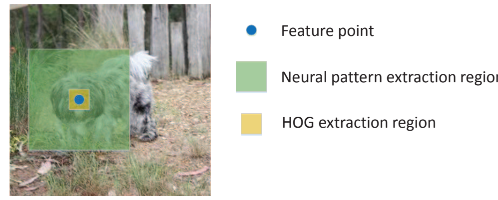


Figure 5. Long-range features for detection from higher layers of convolutional networks: The blue circle shows the feature point at which we want to extract features. The yellow patch shows the area where HOG features are built (usually 8×8). The green patch is the receptive field from which the deep net features are are extracted (163×163 for the fifth convolutional layer).

Long-range context modeling From lower to higher layers, DNP features cover increasingly larger receptive fields. On the fifth layer, each neuron is responsive to a spatial area of 163×163 pixels in the input image. The features in this layer reacts to appearances of much larger scale as compared to hand-designed local features like HOG for object detection as shown in Figure 5. The long-range effect of the significantly larger context area is beneficial. It is analogous to long-range effects which were shown to improve localization (Criminisi et al., 2009) and image segmentation (Lezama et al., 2011).

3.3. Regionlets with Local Histograms of Dense Neural Patterns

The *Regionlets* approach for object detection was recently proposed in (Wang et al., 2013). Compared to classical detection methodologies, which apply a object classifier on dense sliding windows (Felzenszwalb et al., 2010; Dalal & Triggs, 2005), the approach employs candidate bounding boxes from Selective Search (Van de Sande et al., 2011). Given an image, candidate boxes, *i.e.*, object hypothesis are proposed using low-level segmentation cues.

The *Regionlets* approach employs boosting classifier cascades as the window classifier. The input to each weak classifier is a one-dimensional feature from an arbitrary region R. The flexibility of this framework emerges from max-

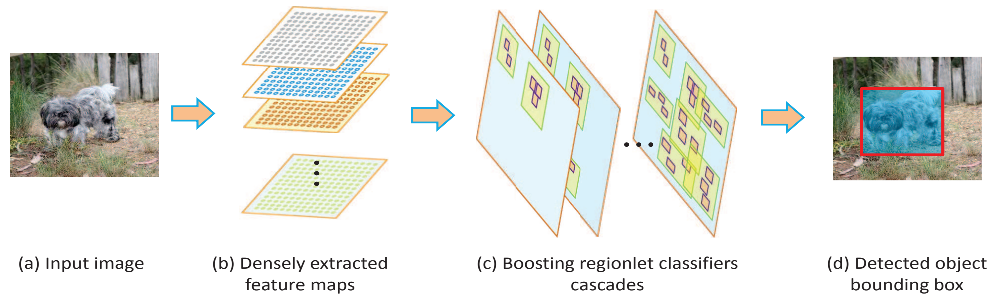


Figure 6. Regionlets object detection framework. It learns cascaded boosting classifiers to detect objects of interest. The object searching space is defined using segmentation cues.

pooling features from several sub-regions inside the region R. These sub-regions are named *Regionlets*. In the learning process, the most discriminative features are selected by boosting from a large feature pool. It naturally learns deformation handling, one of the challenges in generic object detection. The *Regionlets* approach offers the powerful flexibility to handle different aspect ratios of objects. The algorithm is able to evaluate any rectangular bounding box. This is because it removes constraints that come with fixed grid-based feature extraction.

The dense neural patterns introduced in 3.2 encode high-level features from a deep CNN at specific coordinates on the detection image. This makes them a perfect set of features for the *Regionlets* framework. The basic feature construction unit in the *Regionlets* detection model, *i.e.* a regionlet, varies in scales and aspect ratios. At the same time, the deep neural patterns from an image are extracted using a fixed stride which leads to evenly distributed feature points in both horizontal and vertical directions. As illustrated in Figure 7, a regionlet can cover multiple feature points or no feature point. To obtain a fixed length visual representation for a regionlet of arbitrary resolution, we build a local DNP histogram, or average pooling of DNPs, inside each regionlet. Denote DNPs in a regionlet r as $\{\mathbf{x}_i | i \in (1, \dots N_r)\}$, where i indicates the index of the feature point, N_r is the total number of feature points in regionlet r. The final feature for r is computed as:

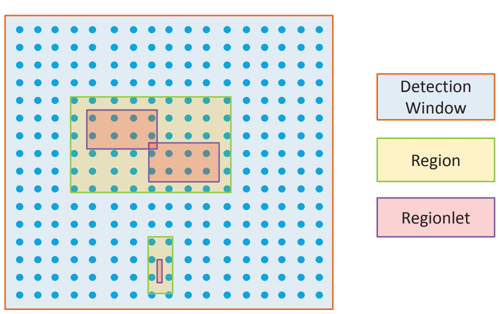


Figure 7. Illustration of feature points, a detection window, regions, and regionlets. Blue points represent dense neural patterns extracted in each spatial location. The figure shows that a regionlet can spread across multiple feature points, or no feature point.

$$\mathbf{x} = \frac{1}{N_r} \sum_{i=1}^{N_r} \mathbf{x}_i. \tag{3}$$

Each dimension of the deep neural patterns corresponds to a histogram bin and their values from different spatial locations are accumulated inside a regionlet. The histograms are normalized using L-0 norm. While most histogram features define a fixed spatial resolution for feature extraction, our definition allows for a histogram over a region of arbitrary shape and size. Following (Wang et al., 2013), max-pooling is performed among regionlets to handle local deformations.

To incorporate DNP into the *Regionlets* detector learning framework, in which the weak learner is based on a 1-D feature, we uniformly sample the *DNP*$\times$*Regionlets* configuration space to construct the weak classifier pool. Each configuration specifies the spatial configuration of *Regionlets* as well as the feature dimension of *DNP*. Because the representation is 1-D, the generated feature pool can be easily augmented to the pool of other features such as HOG, LBP or Covariance.

Constructing DNP feature representations for other template-based detectors (similar as HOG template) is fairly simple. Naturally we just need to concatenate all DNPs in the detection window. The features can also be directly applied to the Deformable Part-based Model by replacing the HOG features with the 256 dimensional neural patterns.

4. Experiments

To validate our method, we conduct experiments on the PASCAL VOC 2007 and VOC 2010 object detection benchmarks, following standard evaluation protocols. PASCAL VOC datasets contain 20 categories of objects. The performance on these datasets is measured by mean average precision (mAP) over all classes. In the follow-

Table 2. Detection results on PASCAL VOC 2007 using different layers of neural patterns as the feature for the *Regionlets* framework.

	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	***mAP***
Layer 1	31.5	28.9	8.1	12.7	1.2	32.9	46.3	29.6	4.2	18.3	28.2	17.2	46.3	40.6	36.1	8.2	21.6	17.5	41.7	25.8	24.9
Layer 2	40.1	46.2	16.6	15.6	5.3	44.3	48.7	42.8	9.9	31.6	36.2	27.8	58.1	48.4	39.8	9.1	29.6	28.7	53.6	37.2	33.5
Layer 3	39.1	45.2	18.3	16.3	4.7	46.9	47.1	45.3	9.3	31.6	42.2	31.4	57.0	50.5	41.4	12.8	26.6	28.8	54.6	40.7	34.5
Layer 4	**45.0**	53.8	21.2	17.5	**8.1**	**51.3**	50.3	52.7	12.6	32.5	44.3	39.3	62.4	**54.8**	42.3	14.1	**33.5**	40.8	60.3	40.9	38.9
Layer 5	44.6	**55.6**	**24.7**	**23.5**	6.3	49.4	**51.0**	**57.5**	**14.3**	**35.9**	**45.9**	**41.3**	**61.9**	54.7	**44.1**	**16.0**	28.6	**41.7**	**63.2**	**44.2**	**40.2**

ing paragraphs, we describe the experimental set-up, results and analysis for our object detection approach.

We train deep neural network with five convolutional layers and three fully connected layers on 1.2 million images in ILSVRC 2010. All input images are center-cropped and resized to 256×256 pixels. The CNN was trained on a NVIDIA Tesla K20c GPU. To improve invariance in our DNP features, we augment the data with image distortions based on translations and PCA on color channels. After training for 90 epochs, the deep CNN reached 59% top 1 accuracy, within a few percent of the performance in (Krizhevsky et al., 2012) on the ILSVRC 2010 test set. While our aim is to demonstrate the effectiveness of DNPs in object detection, a deep CNN with better performance is likely to further improve the detection accuracy.

The original *Regionlets* (Wang et al., 2013) approach utilizes three different features, HOG, LBP and covariance. In our experiments, we add to the feature pool DNP features from different layers. During cascade training, 100 millions candidate weak classifiers are generated from which we sample 20K weak classifiers. On each test image, we form proposed object hypothesis as (Van de Sande et al., 2011) and pass them along the cascaded classifiers to obtain final detection result.

4.1. Detection Performance

We firstly evaluate how the deep neural patterns alone perform with the *Regionlets* framework, followed with evaluation of the combination of DNP and HOG, LBP, Covariance features. Finally, we compare our method with other state-of-the-art approaches.

Table 2 presents the detection performance using dense neural patterns extracted from different layers of the deep convolutional neural network on PASCAL VOC 2007 dataset. It shows that the performance increases with respect to the layer hierarchy. DNPs from the fourth layer and the fifth layer have similar performance, both of which are much better then those from lower layers.

Table 3 summarizes the performance(sorted in ascending order) of traditional features, DNP and their combinations on PASCAL VOC 2007. It is interesting that DNPs from the second layer and third layer have comparable performance with the well engineered features such as HOG,

Table 3. Detection results using traditional feature and Deep Neural Patterns on PASCAL VOC 2007. The combination of traditional features and DNP shows significant improvement.

Features	Mean AP
DNP Layer 1	24.9
DNP Layer 2	33.5
LBP	33.5
Covariance	33.7
DNP Layer 3	34.5
HOG	35.1
DNP Layer 4	38.9
DNP Layer 5	40.2
HOG, LBP, Covariance	41.7
HOG, LBP, Covariance, DNP Layer 5	**46.1**

Table 4. Performance comparison between two feature combination strategies: 1) Combination of neural patterns from the fifth layer and neural patterns from a shallow layer(second layer). 2) Combination of neural patterns from the fifth layer and hand-crafted low-level features.

Features	Mean AP
DNP Layer 5	40.2%
DNP Layer 5 + Layer 2	40.4%
DNP Layer 5 + HOG, LBP, Covariance	46.1%

LBP and Covariance features. DNPs from the fifth layer outperforms any single features, and are comparable to the combination of all the other three features. The most exciting fact is that DNPs and hand-designed features are highly complementary. Their combination boosts the mean average precision to 46.1%, outperforming the original Reginolets approach by 4.4%. Note that we did not apply any fine-tuning of the neural network on the PASCAL dataset.

The combination of DNPs and hand-crafted low-level features significantly improves the detection performance. As aforementioned, low-level DNPs perform similarly as HOG. To determine whether the same synergy can be obtained by combining low-level and high-level DNPs, we combine the DNPs from the fifth convolutional layer and the second convolutional layer. The performance is shown in Table 4. However, the combination only performs slightly better (0.2%) than using the fifth layer only. This may be because the fifth layer features are learned from the lower level which makes these two layer features less complementary.

Table 5. Detection results(mean average precision%) on PASCAL VOC 2007 and VOC 2010 datasets. **DPM:** Deformable Part-based Model (Felzenszwalb et al., 2010);**SS_SPM:** Selective Search with Spatial Pyramid Matching (Van de Sande et al., 2011);**Objectness:** (Alexe et al., 2012); **BOW:** (Vedaldi et al., 2009); **Regionlets:**Regionlets method with HOG, LBP Covariance feature (Wang et al., 2013), **DNP+ Regionlets:**Regionlets method with HOG, LBP Covariance feature and DNPs.**R-CNN pool$_5$**: Region based classification for detection (Girshick et al., 2013) with features from the fifth convolutional layer with max pooling. **R-CNN FT fc$_7$:** Region based classification for detection (Girshick et al., 2013) with features from the full connected layer fine-tuned on the PASCAL VOC datasets.

	VOC 2007	VOC2010
DPM	33.7	29.6
SS_SPM	33.8	34.1
Objectness	27.4	N/A
BOW	32.1	N/A
Regionlets	41.7	39.7
R-CNN pool$_5$	40.1	N/A
R-CNN FT fc$_7$	**48.0**	43.5
DNP+Regionlets	46.1	**44.1**

Table 5 shows detection performance comparison with other detection methods on PASCAL VOC 2007 and VOC 2010 datasets. We achieved 46.1% and 44.1% mean average precision on these two datasets which are comparable with or better than the current stat of the art by (Girshick et al., 2013). Here we compare to results with two different settings in (Girshick et al., 2013): features from the fifth convolutional layer after pooling, features from the seventh full connected layer with fine-tuning on the PASCAL datasets. The first setting is similar to us except that features are pooled. Our results are better(46.1% vs 40.1% on VOC 2007) than (Girshick et al., 2013) on both datasets in this setting. The approach in (Girshick et al., 2013) requires resizing a candidate region and apply the deep CNN thousands of times to extract features from all candidate regions in an image. The complexity of our method is independent of the number of candidate regions which makes it orders of magnitude faster. Table 6 shows the comparison with (Girshick et al., 2013) in terms of speed using the first setting.[5] The experiment is performed by calculating the average time across processing all images in the PASCAL VOC 2007 dataset. DNPs extraction take 1.64 seconds for per image while (Girshick et al., 2013) requires 2 minutes. The numbers are obtained on an Intel Xeon CPU E5-2450 blade server.

[5]The time cost of the second setting in (Girshick et al., 2013) is higher because of the computation in full connected layer.

Table 6. Speed comparison with directly extracting CNN features for object candidates (Girshick et al., 2013) .

	R-CNN pool$_5$	**Ours**
Resize object candidate regions	Yes	No
Number of model convolutions	~ 2213	~ 30
Feature extraction time per image	121.49s	**1.64**s

4.2. Visual Analysis

Is the increase in detection performance by adding dense neural patterns attributable to the high-level cues encoded by DNPs? To answer this question, we devise a visualization techniques for the most important features used by the detector. The learning process for boosting selects discriminative weak classifiers. The importance of a feature dimension roughly corresponds to how frequently it is selected during training. We count the occurrence of each dimension in the final weak classifier set and find the DNP feature dimension most frequently selected by boosting. To visualize these feature dimensions, we retrieve image crops from the dataset which give the highest responses to the corresponding neurons in the deep CNN.

Figure 8 shows the visualization. The ideal case is that the most frequent neural patterns selected in a person detector give high responses to parts belonging to a person. This indicates that the neural patterns encode high-level information. The left column of Figure 8 describes the object category we want to detect. Right columns show visual patches which give high responses to the most frequently selected neural pattern dimension for the category. This analysis indicates that the selected neural patterns encode part-level or object-level visual features highly correlated with the object category. For a dog detector, neural patterns related to a dog face are frequently selected. We also performed a similar analysis with the HOG feature. In comparison, the frequently selected HOG dimension carries a lot less categorical information because gradients are low-level visual features.

5. Conclusion

In this paper, we present a novel framework to incorporate a discriminatively trained deep convolutional neural network into generic object detection. It is a fast effective way to enhance existing conventional detection approaches with the power of a deep CNN. Instantiated with *Regionlets* detection framework, we demonstrated the effectiveness of the proposed approach on public benchmarks. We achieved comparable performance to state-of-the-art with 74 times faster speed on PASCAL VOC datasets. We also show that the DNPs are complementary to traditional features used in object detection. Their combination significantly boosts the performance of each individual feature.

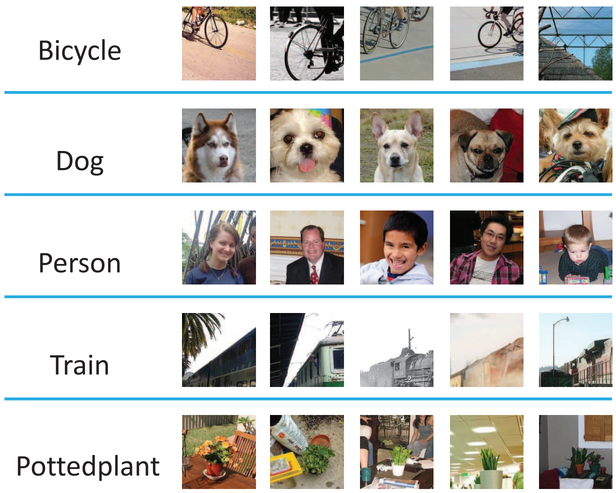


Figure 8. Visualization of the high-level information encoded by neural patterns from the fifth convolutional layer. The patches are obtained by: 1) Determine the most frequently selected neural pattern dimension (1 out of 256) for an object category. 2) Run the neural pattern extractor as a detector, using the value of the extracted neural patterns as detection scores. 3) Collect and rank detection results, visual patches with larger neural pattern values are ranked top.

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