GATED MULTI-LAYER CONVOLUTIONAL FEATURE EXTRACTION NETWORK FOR ROBUST PEDESTRIAN DETECTION

Tianrui Liu, Jun-Jie Huang, Tianhong Dai, Guangyu Ren and Tania Stathaki

Department of Electrical and Electronic Engineering
Imperial College London, United Kingdom

ABSTRACT
Pedestrian detection methods have been significantly improved with the development of deep convolutional neural networks. Nevertheless, robustly detecting pedestrians with a large variant on sizes and with occlusions remains a challenging problem. In this paper, we propose a gated multi-layer convolutional feature extraction method which can adaptively generate discriminative features for candidate pedestrian regions. The proposed gated feature extraction framework consists of squeeze units, gate units and a concatenation layer which perform feature dimension squeezing, feature elements manipulation and convolutional features combination from multiple CNN layers, respectively. We proposed two different gate models which can manipulate the regional feature maps in a channel-wise selection manner and a spatial-wise selection manner, respectively. Experiments on the challenging CityPersons dataset demonstrate the effectiveness of the proposed method, especially on detecting those small-size and occluded pedestrians.

Index Terms—Pedestrian detection, gated network, squeeze network, multi-layer convolutional features.

1. INTRODUCTION
Pedestrian detection has long been an attractive topic in computer vision with significant impact on both research and industry. Pedestrians detection is essential for scene understanding, and has a wide applications such as video surveillance, robotics automation and intelligence driving assistance systems. The pedestrian detection task is often challenged by a pedestrians with large variation of poses, appearances, sizes and under real life scenarios with complex backgrounds.

Traditional pedestrian detectors [1,6] exploit various hand-engineered feature representations, such as Haar [7], local binary pattern [8] as well as the Histogram of Oriented Gradient (HOG) feature and its variations. These feature representations are used in conjunction with a classifier, for instance support vector machine [9] and boosted forests [10].

This work was supported by the EU H2020 TERPSICHORE project “Transforming Intangible Folkloric Performing Arts into Tangible Choreographic Digital Objects” under the grant agreement 691218.

to perform pedestrian detection via classification. Recent advances of deep neural networks have made significant improvements on pedestrian detection methods [11–15]. Zhang et al. [13] tailored the well known Faster-RCNN [16] object detector in terms of anchors and feature strides to accommodate for pedestrian detection problems. Multi-layer Channel Features (MCF) [17] and RPN+BF [11] proposed to concatenate feature representations from multiple layers of a Convolutional Neural Network (CNN) and replace the downstream classifier of Faster R-CNN with boosted classifiers to improve the performance on hard sample detection. Compared to the traditional methods, CNN-based methods are equipped with more powerful feature representation. The challenge of pedestrian detection regrading pose and appearance variations can be addressed well in most circumstances. While there is still a lot of room for improvement for detecting pedestrian under large variations in scale.

The visual appearance and the feature representation of large-size and small-size pedestrians are significantly different. For this reason, it is intuitive to use different feature representation for detecting objects of different sizes. In [15], it has been claimed that the features that can best balance feature abstraction level and resolution are from different convolutional layers. A Scale-Aware Multi-resolution (SAM) CNN-method [15] was proposed which achieves good feature representation by choosing the most suitable feature combination for pedestrians of different sizes from multiple convolutional layers. The limitation of this method is that how the multi-layer feature is combined is hand-designed. Hence, there has only be a limited number of heuristic and fixed feature combinations.

In this paper, we aim at investigating a more advanced approach which can automatically select combinations of multi-layer features for detecting pedestrians of various sizes. A pedestrian proposal network is used to generate pedestrian candidates and thereafter we propose a gated feature extraction network which can adaptively provide discriminative features for the pedestrian candidates of different size. In the proposed gated multi-layer feature extraction framework, a squeeze unit is applied to reduce the dimension of Region of Interests (RoI) feature maps pooled from each convolutional layer. It is an essential component in the gated feature ex-
network \cite{18} as the backbone network. There are 13 convolutional layers in VGG16 which can be regarded as five convolutional blocks, i.e., Conv1, Conv2, Conv3, Conv4, and Conv5. Features from different layers of a CNN represent different levels of abstraction and meanwhile has different reception fields which can provide different cues for pedestrian detection. Our gated network takes the features from all the five convolutional layers as the input and will thereafter select the most discriminative feature component for pedestrian candidate of different size. A Region Proposal Network (RPN) is used to generate a number of candidate pedestrian proposals. Given the candidate proposals, the gated multi-layer feature extraction network manipulates the CNN feature maps from each convolutional block and generates representative features for each region of interest (RoI).

The proposed gated multi-layer feature extraction network helps to realize an automatic re-weighting of multi-layer convolutional features. Nevertheless, the gated network requires additional convolutional layers which induce a deeper RoI-wise sub-network at the cost of higher complexity and higher memory occupation. To remedy this issue, our gated sub-network includes a squeeze unit which reduces the dimension of the feature maps.

As illustrated in Fig. 1, features maps from each convolutional block of the backbone network are first compressed by a squeeze unit, then the RoI features pooled from the squeezed lightweight feature maps are passed through gate units for feature selection, and finally integrated at the concatenation layer.

### 2.2. The Squeeze Unit

A squeeze unit is used to reduce the input feature dimension of the RoI-wise sub-network in the proposed gated feature extraction network. Let us denote the input feature maps as \( F = [ f_1, \ldots, f_{C_{in}} ] \in \mathbb{R}^{H \times W \times C_{in}} \) which has spatial size \( H \times W \) and is of \( C_{in} \) channels. The squeeze unit will map the input feature maps \( F \in \mathbb{R}^{H \times W \times C_{in}} \) to the lightweight output feature maps \( \hat{F} = [ \hat{f}_1, \ldots, \hat{f}_{C_{out}} ] \in \mathbb{R}^{H \times W \times C_{out}} \) with \( C_{out} < C_{in} \) by applying 1 by 1 convolution, i.e.,

\[
\hat{f}_i = v_i \ast F, \tag{1}
\]

where \( v_i \) is the \( i \)-th learned filter in the squeeze network for \( i = 1, \ldots, C_{out} \), and ‘\( \ast \)’ denotes convolution.

The squeeze ratio is defined as \( r = C_{in}/C_{out} \). In Section 3.2 we will show that a properly selected squeeze ratio \( r \) will reduce the RoI-wise sub-network parameters without noticeable performance deduction.

RoI-pooling \cite{16} will be performed on the squeezed lightweight feature maps. The features then pass through a gate unit for feature selection. The gate units manipulates the CNN features to highlight the most suitable feature channels or feature components for a particular RoI, while suppressing the redundant or unimportant ones.


2.3. The Gate Unit

A gate unit will be used to manipulate RoI features pooled from the squeezed lightweight convolutional feature maps. Generally, a gate unit consists of a convolutional layer, two fully connected (fc) layers and a Sigmoid function at the end for output normalization. Given regional feature maps \( R \), the output of a gate unit \( G \in \mathbb{R}^{h_g \times w_g \times c_g} \) can be expressed as:

\[
G = \sigma(\hat{W}_3 \delta(\hat{W}_2 \delta(\hat{W}_1 * R))),
\]

where \( \sigma(\cdot) \) denotes the Sigmoid function, \( \delta(\cdot) \) denotes the ReLU activation function [19], and \( \hat{W} = \{ \hat{W}_1, \hat{W}_2, \hat{W}_3 \} \) are the learnable parameters of the gate network.

The output of a gate unit \( G \) is used to manipulate the regional feature maps \( R \) through an element-wise product:

\[
\hat{R} = G \odot R,
\]

where \( \odot \) denotes the element-wise product.

The manipulated features outputs from a gate network \( \hat{R} \) will have the same size as its input RoI feature \( R \), and will enhance the information that is helpful for identifying the pedestrian within this RoI. We have designed two type gate units based on how the RoI feature maps will be manipulated, namely, the spatial-wise selection gate model and the channel-wise selection gate model. The channel-wise selection gate model are able to increase the inter-dependencies among different features channels, while the spatial-wise selection gate model enhance the feature capacity in terms of spatial locations.

2.3.1. Spatial-wise selection gate module

The gate unit for spatial-wise selection outputs a 2-dimensional (2D) map \( G \) of size \((h_g, w_g, c_g) = (h, 1, 1)\). It will perform an element-wise product with the RoI feature maps \( R \) which is of size \( h \times w \times c \) through a 1 by 1 convolution. As shown in Figure 2 through 1 by 1 convolution, the resulting 2D map has the same spatial resolution as the input feature maps. The 2D map is then passed through two fully connected (fc) layers and a Sigmoid function for normalization. The obtained 2D spatial mask \( G \) will be used to modulate the feature representation for every spatial location of the input feature. The feature values from all \( C \) feature channels at spatial location \((i, j)\) will be modulated by the coefficient \( G(i, j, 1)\).

2.3.2. Channel-wise selection gate module

The gate model for channel-wise section generates a vector of size \((h_g, w_g, c_g) = (1, 1, C)\) through depth-wise separable convolution [20]. As shown in Figure 3 this vector is further passed through two fc layers and a Sigmoid function. The obtained \( G \) thereafter is used to perform a modulation with the convolutional features along the channel dimension. All the feature values within the \( k \)-th \((k \in [1, C])\) channel will be modulated by the \( k \)-th coefficient of \( G(1, 1, k)\).

3. EXPERIMENTS

3.1. Dataset and Experimental Setups

CityPersons [13] is a recent pedestrian detection dataset built on top of the CityScapes dataset [21] which is for semantic segmentation. The dataset includes 5,000 images captured in several cities of Germany. There are about 35,000 persons with additional around 13,000 ignored regions in total. Both bounding box annotation of all persons and annotation of visible person parts are provided. We conduct our experiments on CityPersons using the reasonable train/validation sets for training and testing, respectively.

Evaluation metrics: Evaluations are measured using the log average missing rate (MR) of false positive per image (FPI) ranging from \(10^{-2}\) to \(10^{2}\) (\(MR_{-2}\)). We evaluated four subsets with different ranges of pedestrian height (hgt) and different visibility levels (vis) as follows:

1. All: \(hgt \in [20, \inf] \) and \(vis \in [0.2, \inf]\),
2. Small (Sm): \(hgt \in [50, 75] \) and \(vis \in [0.65, \inf]\),
3. Occlusion (Occ): \(hgt \in [50, \inf] \) and \(vis \in [0.2, 0.65]\),
4. Reasonable (R): \(hgt \in [50, \inf] \) and \(vis \in [0.65, \inf]\).

Network training and experimental setup: The loss function contains a classification loss term and a regression loss.
Table 1. Missing rate (MR%) on Citypersons validation set using different squeeze ratios $r$.

| squeeze ratio | All   | Small | Occlusion | Reasonable |
|---------------|-------|-------|-----------|------------|
| $r = 1$       | 43.70 | 39.65 | 56.97     | 14.49      |
| $r = 2$       | 43.02 | 42.02 | 55.60     | 14.35      |
| $r = 4$       | 42.93 | 44.33 | 56.34     | 14.63      |
| $r = 8$       | 44.52 | 39.98 | 58.06     | 14.85      |

Table 2. Comparison of pedestrian detection performance (in terms of MR%) of our proposed gate model with state-of-the-arts (in terms of MR%) on the CityPersons dataset.

| Model                  | All     | Sm      | Occ     | R     |
|------------------------|---------|---------|---------|-------|
| FRCNN [Baseline]       | 44.6    | 40.46   | 56.19   | 16.44 |
| Adapted FRCNN [13]     | -       | -       | -       | 15.40 |
| Repulsion Loss [24]    | 44.45   | 42.63   | 56.85   | 13.22 |
| OR-CNN [25]            | 42.32   | 42.31   | 55.68   | 12.81 |
| Spatial-wise gate       | 41.72   | 39.46   | 52.18   | 14.01 |
| Channel-wise gate       | 41.76   | 37.62   | 53.53   | 13.49 |

3.2. Effectiveness of Squeeze Ratio

The squeeze ratio $r$ affects the network in terms of feature capacity and computational cost. To investigate the effects of squeeze ratio, we conduct experiments using features from multiple convolutional layers that have been squeeze by $r = 1, 2, 4, 8$ which will reduce the number of parameters in the following RoI-wise sub-networks by a factor of 1, 2, 4 and 8, accordingly. The performances are compared in Table 3.2. We find that squeeze network can reduce the RoI-wise sub-network parameters without noticeable performance deduction. We use the reduction ratio $r = 2$ which is a good trade-off between performance and computational complexity.

3.3. Effectiveness of the Proposed Gate Models

Baseline: we use a modified version of the Faster-RCNN [16] as our baseline detector. To generate pedestrian candidates, we use anchors of a single ratio of $\gamma = 0.41$ with 9 scales for the region proposal network. The baseline detector only adopts the Conv5 feature maps for feature representation. The limited feature resolution of Conv5 restrains the capability for detecting small pedestrians. We dilate the Conv5 features by a factor of two which enlarges the receptive field without increasing the filter size.

For our “spatial-wise gate” model and “channel-wise gate”, we use features extracted from the proposed gated multi-layer feature extraction network applying the two gate models, respectively. As can be seen from Table 2 both the spatial-wise gate model and the channel-wise gate model make improvements upon the Baseline detector. These results demonstrate the effectiveness of our proposed gated multi-layer feature extraction. More specifically, the spatial-wise gate model achieves better performance on the “Occlusion” subset, while the channel-wise gate model achieves better performance on the “Small” subset.

We also compare our proposed pedestrian detector with several state-of-the-art pedestrian detectors in Table 2 including Adapted FRCNN [13], Repulsion Loss [24], and Occlusion-aware R-CNN (OR-RCNN) [25]. Repulsion Loss [24] and OR-RCNN [25] are recent pedestrian detection methods proposed to address the occlusion problems. For fare comparison, all the performance are evaluated on the original image size ($1024 \times 2048$) of the CityPersons validation dataset. We can observe that both of the two proposed gated models surpass the other approaches under the “All”, “Occlusion” and “Small” settings. The most notable improvements are on the “Occlusion” and the “Small” subsets. Our channel-wise gate model exceed the state-of-the-art method OR-RCNN [24] by a large margin of 4.7% on the “Small” subset, which highlights the effectiveness of our method for small-size pedestrian detection. When it comes to the “Occlusion” subset where includes some severely occluded pedestrian, our spatial-wise gate model achieves the best MR$_{-2}$ performance of 52.18%, surpassing the second best pedestrian detector by 2.5%.

4. CONCLUSIONS

In this paper, we proposed a gated multi-layer convolutional feature extraction network for robust pedestrian detection. Convolutional features from backbone network are fed into the gated network to adaptively select discriminative feature representations for pedestrian candidate regions. A squeeze unit for feature dimension reduction is applied before the gated unit for RoI-wise feature manipulation. Two types of gate models that we proposed can manipulate the feature maps in channel-wise manner and in spatial-wise manner, respectively. Experiment on the CityPersons pedestrian dataset demonstrate the effectiveness of the proposed method for robust pedestrian detection.
5. REFERENCES

[1] Navneet Dalal and Bill Triggs, “Histograms of oriented gradients for human detection,” in Computer Vision and Pattern Recognition (CVPR), 2005 IEEE Conference on. 2005, vol. 1, pp. 886–893, IEEE.

[2] Piotr Dollár, Ron Appel, Serge Belongie, and Pietro Perona, “Fast feature pyramids for object detection,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, no. 8, pp. 1532–1545, 2014.

[3] Jiayuan Mao, Tete Xiao, Yuning Jiang, and Zhimin Cao, “What can help pedestrian detection?,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.

[4] Shanshan Zhang, Rodrigo Benenson, Mohamed Omran, Jan Hendrik Hosang, and Bernt Schiele, “How far are we from solving pedestrian detection?,” CoRR, vol. abs/1602.01237, 2016.

[5] Pedro F Felzenszwalb, Ross B Girshick, David McAllester, and Deva Ramanan, “Object detection with discriminatively trained part-based models,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 32, no. 9, pp. 1627–1645, 2010.

[6] Tianrui Liu and Tania Stathaki, “Fast head-shoulder proposal for deformable part model based pedestrian detection,” in 2016 IEEE International Conference on Digital Signal Processing (DSP), Oct 2016, pp. 457–461.

[7] Michael Oren, Constantine Papageorgiou, Pawan Sinha, Edgar Osuna, and Tomaso Poggio, “Pedestrian detection using wavelet templates,” in cvpr, 1997, vol. 97, pp. 193–199.

[8] Timo Ojala, Matti Pietikainen, and Topi Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971–987, 2002.

[9] Corinna Cortes and Vladimir Vapnik, “Support vector machine,” Machine learning, vol. 20, no. 3, pp. 273–297, 1995.

[10] Pierre Geurts, Damien Ernst, and Louis Wehenkel, “Extremely randomized trees,” Machine learning, vol. 63, no. 1, pp. 3–42, 2006.

[11] Liliang Zhang, Liang Lin, Xiaodan Liang, and Kaiming He, “Is Faster R-CNN doing well for pedestrian detection?,” CoRR, vol. abs/1607.07032, 2016.

[12] J. Li, X. Liang, S. Shen, T. Xu, J. Feng, and S. Yan, “Scale-aware Fast R-CNN for pedestrian detection,” IEEE Transactions on Multimedia, vol. 20, no. 4, pp. 985–996, April 2018.

[13] Shanshan Zhang, Rodrigo Benenson, and Bernt Schiele, “Citypersons: A diverse dataset for pedestrian detection,” CoRR, vol. abs/1702.05693, 2017.

[14] T. Liu and T. Stathaki, “Enhanced pedestrian detection using deep learning based semantic image segmentation,” in 2017 22nd International Conference on Digital Signal Processing (DSP), Aug 2017, pp. 1–5.

[15] Tianrui Liu, Mohamed Elmikaty, and Tania Stathaki, “SAM-RCNN: Scale-aware multi-resolution multi-channel pedestrian detection,” in British Machine Vision Conference (BMVC), September 2018.

[16] Shaqing Ren, Kaiming He, Ross Girshick, and Jian Sun, “Faster R-CNN: Towards real-time object detection with region proposal networks,” in Advances in neural information processing systems, 2015, pp. 91–99.

[17] Jiale Cao, Yanwei Pang, and Xuelong Li, “Learning multilayer channel features for pedestrian detection,” IEEE transactions on image processing, vol. 26, no. 7, pp. 3210–3220, 2017.

[18] Karen Simonyan and Andrew Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[19] Vinod Nair and Geoffrey E Hinton, “Rectified linear units improve restricted boltzmann machines,” in Proceedings of the 27th international conference on machine learning (ICML-10), 2010, pp. 807–814.

[20] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam, “Mobilenets: Efficient convolutional neural networks for mobile vision applications,” arXiv preprint arXiv:1704.04861, 2017.

[21] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Scharwächter, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele, “The cityscapes dataset,” in CVPR Workshop on The Future of Datasets in Vision, 2015.

[22] Ross Girshick, “Fast R-CNN,” in International Conference on Computer Vision (ICCV), 2015.

[23] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: A Large-Scale Hierarchical Image Database,” in Computer Vision and Pattern Recognition (CVPR), 2009 IEEE Conference on, 2009.

[24] Xilong Wang, Tete Xiao, Yuning Jiang, Shuai Shao, Jian Sun, and Chunhua Shen, “Repulsion loss: Detecting pedestrians in a crowd,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 7774–7783.

[25] Xiao Bian Zhen Lei Stan Z. Li Shifeng Zhang, Longyin Wen, Xinlong Wang, Tete Xiao, Yuning Jiang, Shuai Shao, Jian Sun, J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: A Large-Scale Hierarchical Image Database,” in Computer Vision and Pattern Recognition (CVPR), 2009 IEEE Conference on, 2009.