Analysis of Regionlets for Pedestrian Detection

Niels Ole Salscheider[1], Eike Rehder[2] and Martin Lauer[2]
[1]*FZI Forschungszentrum Informatik at Karlsruhe Institute of Technology (KIT), 76131 Karlsruhe, Germany*
[2]*Department of Measurement and Control (MRT), Karlsruhe Institute of Technology (KIT), 76131 Karlsruhe, Germany*
salscheider@fzi.de, eike.rehder@kit.edu, martin.lauer@kit.edu

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Abstract: Human detection in camera images is an important task for many autonomous robots as well as automated driving systems. The Regionlets detector was one of the best-performing approaches for pedestrian detection on the KITTI dataset when we started this work in 2015.
We analysed the Regionlets detector and its performance. This paper discusses the improvements in accuracy that were achieved by the different ideas of the Regionlets detector. It also analyses what the boosting algorithm learns and how this relates to the expectations.
We found that the random generation of *regionlet configurations* can be replaced by a regular grid of regionlets. Doing so reduces the dimensionality of the feature space drastically but does not decrease detection performance. This translates into a decrease in memory consumption and computing time during training.

1 INTRODUCTION

Many autonomous robots as well as automated driving systems require an accurate and fast pedestrian detector. Such systems can only avoid collisions if the locations of all pedestrians can be determined precisely.

Even though there are very reliable techniques for face detection, pedestrian detection from camera images remains a challenging problem. This is because the body of a pedestrian is deformable and the relative positions of body parts can vary to some degree. In contrast, faces are mostly rigid.

Another challenge is that pedestrians can be seen from arbitrary angles in road scenes. This problem requires either an ensemble of different detectors for the different viewing angles or an approach that can cope with the difference in appearance.

Earlier approaches to solve these tasks include Deformable Part Models (DPM) (Felzenszwalb et al., 2008) and Bag of Words (BoW) (Vogel and Schiele, 2007) models. Both methods can handle some degree of deformation by breaking objects into parts. DPM learns a root filter for the complete object and filters for all object parts. For detection, an exhaustive search for all of these filters is performed. DPM also learns latent variables to describe the relative locations of these parts. These are used to calculate the final detection score.

BoW methods extract features from image patches and cluster the extracted features to determine the words in the codebook. Then a histogram over the occurrence of these words is calculated and used as input for a classifier. In contrast to DPM, BoW methods ignore the spatial relationships between the image patches. This makes the detector insensitive to deformation but a precise localisation of the object is difficult.

A newer approach that also tries to break objects into parts is Regionlets (Wang et al., 2013). It was one of the best-performing techniques for pedestrian detection on the KITTI dataset (Geiger et al., 2012) when we started this work in 2015. During training, this approach generates a large number of regions that cover the complete detection window. A boosting algorithm is used to learn which regions are relevant for the classification problem. The idea behind this is that an object can be decomposed into parts and each selected region corresponds to the area in which such a part can be observed. When the number of generated regions is large enough it is likely that the generated set also contains regions that are close to optimal.

Each region is divided into *regionlets*. Classic features are extracted from each regionlet and max-pooling is performed on all feature vectors extracted in a region. This allows the object part to occur in any regionlet of the region and makes the detector robust to local deformations. Again, the most relevant

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regionlet configurations for each region are chosen by the boosting algorithm from a large number of randomly generated configurations.

The authors of (Wang et al., 2013) give a thorough evaluation of the overall detection performance on different datasets in comparison to other well-known approaches. However, the original paper does not contain a break-down of the contributions of the individual ideas. Also, many implementation details are omitted. This leads to the questions why Regionlets achieve good performance and which of the ideas work well.

We analysed the Regionlets approach and the contributions of the individual ideas to the overall improvement in detection performance. Also, we examined what the boosting classifier learned and how that compares to the expectations given by the design ideas.

We could reduce the memory consumption and computation time during training considerably by replacing the randomly generated regionlet configurations by a regular grid of regionlets. Our proposed stereo image based candidate bounding box selection needs little computation time and reduces the number of detector windows that have to be evaluated by a factor of 3 to 5.

The remainder of this paper is laid out as follows: In Section 2, the Regionlets approach is described in detail. Then, our experiments and an analysis of the approach is presented in Section 3. Finally, a conclusion is drawn in Section 4.

2 REGIONLETS

The task of object detection in images can be broken into two sub-tasks. The first is to determine the locations of objects in the image. Then, the class of these objects is determined by a classifier in order to decide if they are of interest.

A possible solution to the first sub-problem is the sliding window approach that performs an exhaustive search of all possible locations and sizes. In the Regionlets approach, however, these candidate bounding box proposals are generated by selective search (van de Sande et al., 2011). This reduces the number of candidate bounding boxes that have to be evaluated to around 1 000-2 000 per image while still achieving high recall.

The main contribution of the Regionlets approach is a new descriptor that is calculated for the candidate bounding boxes. This descriptor contains information about different scales of the image and is insensitive to deformation. The former is achieved by calculating features of regions with different sizes while the latter is achieved by max-pooling.

The resulting feature vector has a very high dimensionality. Therefore, the authors use a cascaded boosting classifier to select only the most discriminative features.

2.1 The Regionlets Descriptor

Most objects can be divided into parts. A pedestrian, for example, might be broken down into the head, the upper body, arms and legs. Usually, the likelihood of such a part to appear at a specific position inside the bounding box of the object is not uniformly distributed. Instead, for each part there is a region relative to the bounding box that covers (nearly) all possible locations of that part.

The Regionlets descriptor is based on this idea. A large number of regions with different sizes and different positions is generated in a sliding window fashion. The feature vector for each candidate bounding box is then calculated by concatenating the feature vectors of all regions. It is then up to the boosting classifier to select the relevant regions.

In each region, there are multiple sub-regions called regionlets that describe a possible location of the object part in the region. A fixed set of regionlets in a region is called a regionlet configuration. In (Wang et al., 2013), regionlet configurations are generated randomly. First, the size for all regionlets in a configuration is fixed randomly and then a random number of regionlets with this size is positioned randomly in the region.

The feature vector of each regionlet configuration is calculated by performing max-pooling over all feature vectors of all regionlets in this configuration. The idea behind this is that it does not matter in which regionlet the object part is, but only whether it is in (at least) one of them or not. The feature vector of a region is the concatenation of the feature vectors of all regionlet configurations of this region. Again, it is up to the boosting classifier to select the relevant regionlet configurations for each region.

Finally, the feature vector of each regionlet is the concatenation of classic appearance features extracted from the image patch corresponding to the regionlet. These appearance features can for example be the HOG (Dalal and Triggs, 2005) and LBP (Ahonen et al., 2004) descriptors.

2.2 The Boosting Classifier

Because of the large number of regions and the randomly generated regionlet configurations, the feature

space is of very high dimensionality. In (Wang et al., 2013), about 100 million real-valued feature prototypes are generated for training.

RealBoost (Schapire and Singer, 1999) is used to train a classifier cascade for the object detector. This allows to only select relevant features and to reject candidate bounding boxes that do not contain a relevant object early.

The weak learners for the boosting cascades are lookup tables similar to (Huang et al., 2004). They are mathematically defined as

$$h(x) = \sum_{o=1}^{n-1} v_o \mathbb{1}(B(x) = o) \quad , \tag{1}$$

where n is the number of bins, v_o is the table entry at the oth position and $\mathbb{1}$ is an indicator function. $B(x)$ maps the input x to a table entry and is usually chosen in a way so that the expected range of x is uniformly distributed to the bins.

During training, the features are first sorted by the Bhattacharyya distance of the posterior probability of positive and that of negative samples. Then, a feature is iteratively selected and a weak learner is trained for it. In each step, all v_o in the lookup table of the weak learner are chosen as $v_o = \frac{1}{2} \ln\left(\frac{U_o^+}{U_o^-}\right)$. Here U_o^+ is the sum of weights of all positive training samples that fall into the oth bin and U_o^- is the sum of weights of all negative samples in that bin. In each step, the weights of the wrongly classified training examples are increased and the weights of the correctly classified training examples are decreased.

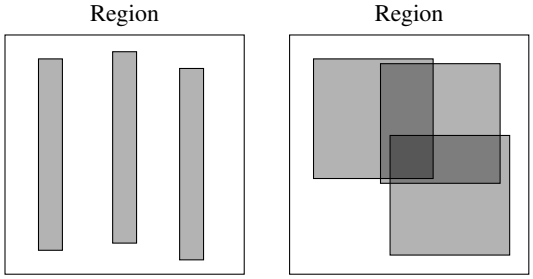
The classification output of the learnt strong classifier for a feature vector $\mathbf{f}$ is then given by $\text{sign}\left(\sum_i h_i(f_i)\right)$.

3 ANALYSIS & EXPERIMENTS

We analysed the Regionlets approach and which influence the different ideas from (Wang et al., 2013) have.

In our implementation, we chose HOG and LBP features as basic appearance features for each regionlet. For HOG, we use 9 equally spaced orientation bins for the unsigned gradient direction. Each regionlet contains one block that is divided into 2×2 cells. The block feature vector is normalised by its L2 norm. Our LBP descriptor considers 8 neighbours with a radius of one. Again, each regionlet contains one block and the corresponding feature vector is normalised by its L1 norm.

We use RealBoost to train a cascade classifier. Our weak learner is a lookup table with 4 entries that correspond to input values in the intervals $[0, 0.25)$, $[0.25, 0.5)$, $[0.5, 0.75)$ and $[0.75, 1]$.



(a) Typically rejected Regionlet configuration. (b) Typically accepted Regionlet configuration.

Figure 1: Examples of regionlet configurations that were used during training. The outer box represents the region while the smaller grey boxes inside represent the regionlets.

The set of regions is generated as follows: Let w_B the width of the candidate bounding box and h_B its height. The set of possible widths w_R of our regions is then $W_R = \{w_B, 0.5w_B, 0.25w_B\}$ and the set of possible heights h_R is $H_R = \{0.5h_B, 0.25h_B, 0.125h_B\}$. We generate regions (x_R, y_R, w_R, h_R) from each element $(h_R, w_R) \in W_R \times H_R$ by using a sliding window approach. The stride is given by $\frac{2w_B}{w_R}$ in x-direction and by $\frac{h_B}{h_R}$ in y-direction.

3.1 Max-Pooling

In our first experiment we generated several regionlet configurations randomly as described in (Wang et al., 2013) and trained the classifier. We then examined which regionlet configurations were chosen by the boosting algorithm.

Figure 1 shows an example of a configuration that was chosen and one that was not chosen. We found that most configurations where the regionlets did not overlap were discarded. In contrast, most of the chosen configurations contained regionlets that had a significant overlap. This is in line with what is intuitively expected: Object parts can usually be found at any position inside the allowed region and not only at a few distinct positions. The chosen regionlet configuration allows for exactly that by performing max-pooling over a large area inside the region.

In order to verify this theory, we replaced all regionlet configurations by an artificial one that only performs max-pooling. It contains 9 regionlets in a 3×3 grid where direct neighbours have 75 % overlap. We found that there was nearly no change in detection performance which confirms our theory.

This is an important observation. When using a regular grid, the dimensionality of the feature space can be reduced by a factor equal to the number of re-

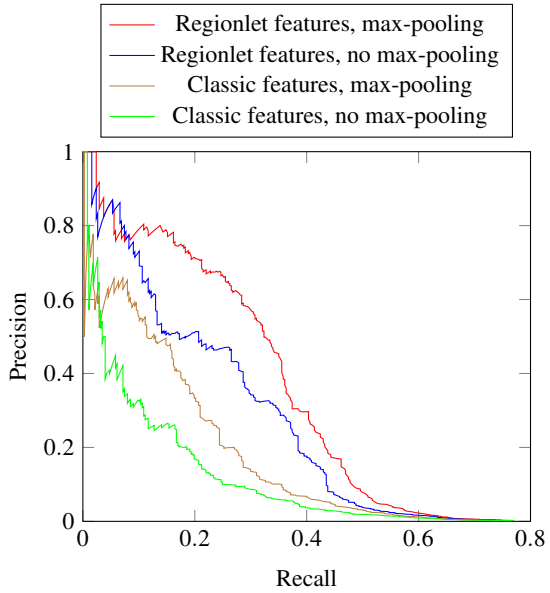


Figure 2: Precision-recall curves of our Regionlets based classifier and a classic approach. The evaluation was performed on 730 randomly chosen images of the KITTI benchmark (Geiger et al., 2012).

gionlet configurations that would be generated otherwise. This translates into a corresponding decrease in memory consumption and computing time during training.

We also evaluated the benefits of max-pooling. We used the KITTI benchmark and selected 730 labelled images randomly for evaluation. All other labelled images were used for training.

Figure 2 shows the precision-recall curves achieved with this. It is clearly visible that max-pooling improves the performance considerably. This is true for both the Regionlets descriptor and a classic descriptor that we used for comparison. The latter is described in detail in the following section.

3.2 Different Scales

One of the most important ideas of the Regionlets descriptor is the introduction of regions that cover the possible locations of all object parts. These regions have different sizes to account for object parts of different sizes and different variability in their possible locations. When all regions are fixed to one size and there is no max-pooling inside the regions, the Regionlet descriptor degrades to a classic block-based descriptor.

We evaluated the benefits of having regions with different sizes by also implementing a classic descriptor and comparing the results. For our classic descriptor, we extract HOG and LBP features from a window

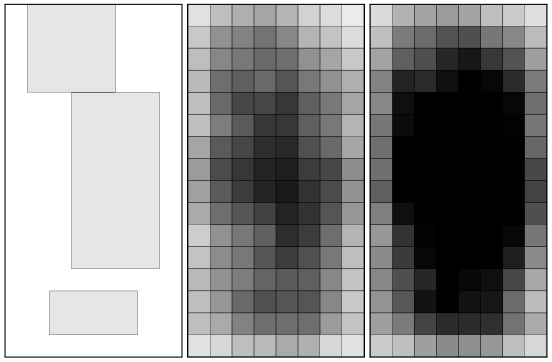


Figure 3: Examples of regions selected by the boosting algorithm. Each region is printed in black but with a low opacity so that overlapping regions can be easily visualised. Therefore, areas where many regions overlap appear darker than those with less overlapping regions. The first image shows the 3 most important regions, the second image the 250 most important regions and the last image the 500 most important regions.

of size 64×128. The block size of the each descriptor is 16×16 and the stride is 8 pixels both in x- and in y-direction. All other parameters match the ones that were used in our Regionlets descriptor.

The results are plotted in Figure 2. The Regionlets descriptor clearly outperforms the classic approach. It can also be seen that the improvement by max-pooling over the pure classic approach is considerably smaller than the improvement by using regions of different sizes.

Figure 3 shows the regions that the boosting classifier selects first, i. e. the most important ones. The three most important regions cover the areas where the upper body, the head and the feet of the pedestrian are expected. Then, the classifier mostly focuses on the upper body. This can be seen when the 250 most import regions are visualised. The 500 most important regions already cover the whole body of the pedestrian. As expected, only very few regions that cover the background are selected.

3.3 Exhaustive Search

The standard approach for object detection in images is the sliding window approach. The detector windows is slid over the image with a fixed stride. Each detector window is evaluated with the classifier to determine whether it contains an object of interest or not. This procedure is repeated with multiple window sizes to search for objects at different scales.

The number of candidate bounding boxes that have to be evaluated can be reduced by using a ground plane assumption. For many applications in traffic, a camera is mounted at a fixed position in the vehicle

and the vehicle can only move on the ground. Therefore, the distance between the camera and the ground is fixed. This is also true for the KITTI dataset. Since pedestrians can also only walk on the ground, some combinations of bounding box position and size are very unlikely to occur.

However, the assumption that the road is a perfect plane may not always hold in curved terrain. Also, pitching of the car may violate a static plane inclination assumption. We handle this by allowing a certain deviation from the perfect plane since we do not want to estimate the ground plane in every shot. This results in a Region Of Interest (ROI) for each scale that has to be searched for pedestrian. We learnt these ROIs from the training images.

The ground plane assumption can be expressed by the following linear equation

$$h = m \cdot u + h_0 \tag{2}$$

where h is the height of the ROI in pixels, u is the lower boundary of the ROI in the image, and m and h_0 are the parameters. We learnt m and h_0 from the training labels by using linear least square estimation. The possible ROI locations are then given by

$$\|m \cdot u + h_0 - h\| < k_1 \tag{3}$$

where k_1 is a non-negative threshold.

On the KITTI dataset, an exhaustive search in all ROIs results in about 10 000 bounding boxes per image that have to be evaluated.

3.4 Selective Search

In (Wang et al., 2013), selective search (van de Sande et al., 2011) is used to reduce the number of candidate bounding boxes that are evaluated. This can help to reduce the required detection run-time. But it can also be beneficial for the precision of the detector since the chance for false positives is reduced. It is, however, important that the recall of the candidate bounding box proposals is very high. The selective search implementation from (van de Sande et al., 2011) generates around 1 000-2 000 candidate bounding boxes per image.

We compared the precision reached when using selective search with a sliding window approach. The results can be found in Figure 4. The precision increased slightly for high decision value thresholds (i. e. where recall is low). However, for lower decision value thresholds the precision decreased. The maximum recall also decreased because the bounding box candidate proposals do not have perfect recall.

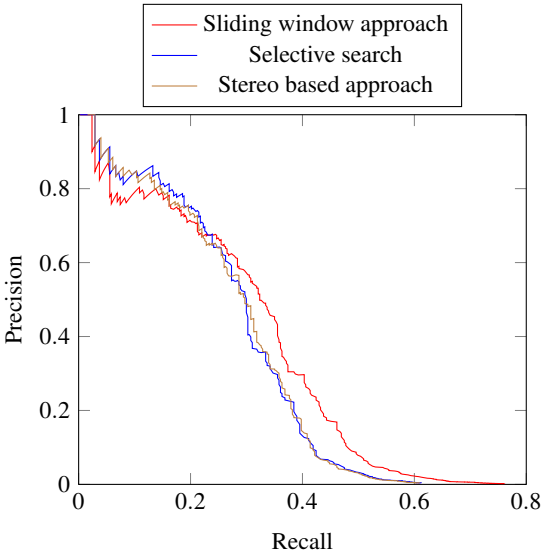


Figure 4: Comparison of precision-recall curves when using selective search, a stereo based approach and a sliding window approach. The evaluation was performed on 730 randomly chosen images of the KITTI benchmark (Geiger et al., 2012).

3.5 Stereo based Bounding Box Proposals

Bounding box proposals can also be generated from stereo image pairs. In general, there are two possibilities to do so. More complex methods take advantage of the fact that there is usually a difference in the depth of an object and its background. Pixels can then be clustered by their depth values and each cluster can be used to generate a bounding box proposal.

The other, simpler, possibility is to assume a fixed size of the searched object in the world. Bounding box candidates can then be generated in a sliding window fashion but all candidates that do not satisfy this assumption are immediately discarded.

We evaluated the performance of the second approach as an alternative to selective search. We assume that a pedestrian has an average size of H in the world. Then, the size h (in pixels) of a person in the image depends on the distance z between camera and this person. The relationship is given by

$$\frac{H}{z} = \frac{h}{f} \tag{4}$$

where f is the focal length of the camera in pixels. Using $H = \text{const.}$ and disparity $d \propto f/z$, we can derive

$$\frac{z \cdot h}{f} \propto \frac{h}{d} = c \tag{5}$$

and thus, we only have to estimate the constant c from

the training data. This again can be done using least squares estimation.

The disparity d is not constant for all pixels in a candidate bounding box. We achieved good results by computing d as the mean disparity of a local neighbourhood at the centre of the candidate bounding box. Then, all candidate bounding boxes for which the following equation holds are discarded:

$$\left\| \frac{h}{d} - c \right\| > k_2 \tag{6}$$

where again, k_2 is a non-negative threshold.

We used (Ranft and Strauß, 2014) to obtain the disparity image. This algorithm focuses on run-time performance while achieving competitive results. However, any other stereo matcher with good run-time performance could be used.

Our stereo based approach reduces the number of candidate bounding boxes per image to about 2 000-3 500 per image. The achieved detection performance is similar to selective search and is plotted in Figure 4.

3.6 Run-time

Our *OpenCL* implementation needs around 700 ms per image on an *Nvidia Titan* graphics card for an exhaustive search using a sliding window approach. The number of evaluated bounding boxes can be drastically reduced by using image segmentation to generate candidate bounding box proposals. This promises to reduce the run-time of the detection algorithm considerably.

However, we found that the code for image segmentation provided with (van de Sande et al., 2011) takes around 1.6 s to execute on our *Intel Xeon E5-2640*. This means that we could not reproduce the performance of (Wang et al., 2013) which reports an overall detection rate of 5 frames per second on a single 2.1 GHz CPU core. It also means that run-time performance cannot be improved by using this original implementation. Other implementations of this algorithm or other approaches for image segmentation can, however, be faster and advantageous for the overall detection run-time.

Our stereo based method for candidate bounding box generation takes approximately 72 ms (65 ms for the stereo matcher and 7 ms for the candidate generation). It reduces the number of evaluated bounding boxes compared to an exhaustive search by a factor of approximately 3 to 5 depending on the image. This results in a corresponding decrease in detector run-time that outweighs the cost of the stereo matching.

4 CONCLUSION

We have analysed the different ideas of the Regionlets approach and determined what makes it work well. The largest improvement in detection performance is achieved by dividing the detection window into regions and learning which of these regions are relevant. We showed that the boosting algorithm learns that the regions that contain parts of the pedestrian's body are the most relevant ones.

Randomly choosing regionlet configurations and performing max-pooling on them achieves a similar performance as max-pooling on a regular grid. The boosting algorithm tends to select configurations that are regular and contain overlapping regionlets. Performing max-pooling on a regular grid decreases the memory consumption and computing time during training.

The performance improvement by max-pooling is less than the improvement achieved by using regions but it is still important. However, it is not specific to the regionlets approach—the same improvement can be seen when max-pooling is used together with classic features (HOG and LBP).

The use of selective search influences the detection performance slightly but it does not necessarily improve it. While it decreases the risk for false positives it also decreases recall. Concerning the run-time performance, selective search does not help in our case. This is because computing the candidate bounding box proposals alone takes more time than an exhaustive search with our *OpenCL* implementation.

However, our stereo based approach for the generation of candidate bounding box proposals is fast enough to improve the overall run-time. With this approach, the overall performance can meet the soft real-time constraints of some applications.

The original Regionlets paper (Wang et al., 2013) omits many implementation details. Therefore, the results are not necessarily comparable with our implementation. We could however show that the Regionlets approach performs much better than classic features.

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