

# Pedestrian Detection: An Evaluation of the State of the Art

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**Abstract**—Pedestrian detection is a key problem in computer vision, with several applications that have the potential to positively impact quality of life. In recent years, the number of approaches to detecting pedestrians in monocular images has grown steadily. However, multiple data sets and widely varying evaluation protocols are used, making direct comparisons difficult. To address these shortcomings, we perform an extensive evaluation of the state of the art in a unified framework. We make three primary contributions: 1) We put together a large, well-annotated, and realistic monocular pedestrian detection data set and study the statistics of the size, position, and occlusion patterns of pedestrians in urban scenes, 2) we propose a refined per-frame evaluation methodology that allows us to carry out probing and informative comparisons, including measuring performance in relation to scale and occlusion, and 3) we evaluate the performance of sixteen pretrained state-of-the-art detectors across six data sets. Our study allows us to assess the state of the art and provides a framework for gauging future efforts. Our experiments show that despite significant progress, performance still has much room for improvement. In particular, detection is disappointing at low resolutions and for partially occluded pedestrians.

**Index Terms**—Pedestrian detection, object detection, benchmark, evaluation, data set, Caltech Pedestrian data set.

## 1 INTRODUCTION

PEOPLE are among the most important components of a machine's environment, and endowing machines with the ability to interact with people is one of the most interesting and potentially useful challenges for modern engineering. Detecting and tracking people is thus an important area of research, and machine vision is bound to play a key role. Applications include robotics, entertainment, surveillance, care for the elderly and disabled, and content-based indexing. Just in the US, nearly 5,000 of the 35,000 annual traffic crash fatalities involve pedestrians [1]; hence the considerable interest in building automated vision systems for detecting pedestrians [2].

While there is much ongoing research in machine vision approaches for detecting pedestrians, varying evaluation protocols and use of different data sets makes direct comparisons difficult. Basic questions such as "Do current detectors work well?" "What is the best approach?" "What are the main failure modes?" and "What are the most productive research directions?" are not easily answered.

Our study aims to address these questions. We focus on methods for detecting pedestrians in individual monocular images; for an overview of how detectors are incorporated into full systems we refer readers to [2]. Our approach is three-pronged: We collect, annotate, and study a large data

set of pedestrian images collected from a vehicle navigating in urban traffic; we develop informative evaluation methodologies and point out pitfalls in previous experimental procedures; finally, we compare the performance of 16 pretrained pedestrian detectors on six publicly available data sets, including our own. Our study allows us to assess the state of the art and suggests directions for future research.

All results of this study, and the data and tools for reproducing them, are posted on the project website: [www.vision.caltech.edu/Image\\_Datasets/CaltechPedestrians/](http://www.vision.caltech.edu/Image_Datasets/CaltechPedestrians/).

### 1.1 Contributions

**Data set.** In earlier work [3], we introduced the Caltech Pedestrian Data Set, which includes 350,000 pedestrian bounding boxes (BB) labeled in 250,000 frames and remains the largest such data set to date. Occlusions and temporal correspondences are also annotated. Using the extensive ground truth, we analyze the statistics of pedestrian scale, occlusion, and location and help establish conditions under which detection systems must operate.

**Evaluation methodology.** We aim to quantify and rank detector performance in a realistic and unbiased manner. To this effect, we explore a number of choices in the evaluation protocol and their effect on reported performance. Overall, the methodology has changed substantially since [3], resulting in a more accurate and informative benchmark.

**Evaluation.** We evaluate 16 representative state-of-the-art pedestrian detectors (previously we evaluated seven [3]). Our goal was to choose diverse detectors that were most promising in terms of originally reported performance. We avoid retraining or modifying the detectors to ensure each method was optimized by its authors. In addition to overall performance, we explore detection rates under varying levels of scale and occlusion and on clearly visible pedestrians. Moreover, we measure localization accuracy and analyze runtime.

To increase the scope of our analysis, we also benchmark the 16 detectors using a unified evaluation framework on

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Fig. 1. Example images (cropped) and annotations from six pedestrian detection data sets. We perform an extensive evaluation of pedestrian detection, benchmarking 16 detectors on each of these six data sets. By using multiple data sets and a unified evaluation framework we can draw broad conclusion about the state of the art and suggest future research directions.

six additional pedestrian detection data sets, including the ETH [4], TUD-Brussels [5], Daimler [6], and INRIA [7] data sets and two variants of the Caltech data set (see Fig. 1). By evaluating across multiple data sets, we can rank detector performance and analyze the statistical significance of the results and, more generally, draw conclusions both about the detectors and the data sets themselves.

Two groups have recently published surveys which are complementary to our own. Geronimo et al. [2] performed a comprehensive survey of pedestrian detection for advanced driver assistance systems, with a clear focus on full systems. Enzweiler and Gavrila [6] published the Daimler detection data set and an accompanying evaluation of three detectors, performing additional experiments integrating the detectors into full systems. We instead focus on a more thorough and detailed evaluation of state-of-the-art detectors.

This paper is organized as follows: We introduce the Caltech Pedestrian Data Set and analyze its statistics in Section 2; a comparison of existing data sets is given in Section 2.4. In Section 3, we discuss evaluation methodology in detail. A survey of pedestrian detectors is given in Section 4.1 and in Section 4.2 we discuss the 16 representative state-of-the-art detectors used in our evaluation. In Section 5, we report the results of the performance evaluation, both under varying conditions using the Caltech data set and on six additional data sets. We conclude with a discussion of the state of the art in pedestrian detection in Section 6.

## 2 THE CALTECH PEDESTRIAN DATA SET

Challenging data sets are catalysts for progress in computer vision. The Barron et al. [8] and Middlebury [9] optical flow data sets, the Berkeley Segmentation Data Set [10], the

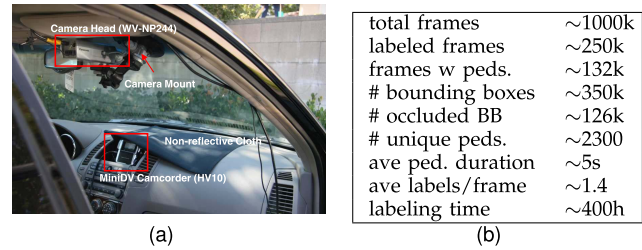


Fig. 2. Overview of the Caltech Pedestrian Data Set. (a) Camera setup. (b) Summary of data set statistics ( $1k = 10^3$ ). The data set is large, realistic, and well annotated, allowing us to study statistics of the size, position, and occlusion of pedestrians in urban scenes and also to accurately evaluate the state of the art in pedestrian detection.

Middlebury Stereo Data Set [11], and the Caltech 101 [12], Caltech 256 [13], and PASCAL [14] object recognition data sets all improved performance evaluation, added challenge, and helped drive innovation in their respective fields. Much in the same way, our goal in introducing the Caltech Pedestrian Data Set is to provide a better benchmark and to help identify conditions under which current detectors fail and thus focus research effort on these difficult cases.

### 2.1 Data Collection and Ground Truthing

We collected approximately 10 hours of 30 Hz video ( $\sim 10^6$  frames) taken from a vehicle driving through regular traffic in an urban environment (camera setup shown in Fig. 2a). The CCD video resolution is  $640 \times 480$ , and, not unexpectedly, the overall image quality is lower than that of still images of comparable resolution. There are minor variations in the camera position due to repeated mountings of the camera. The driver was independent from the authors of this study and had instructions to drive normally through neighborhoods in the greater Los Angeles metropolitan area chosen for their relatively high concentration of pedestrians, including LAX, Santa Monica, Hollywood, Pasadena, and Little Tokyo. In order to remove effects of the vehicle pitching and thus simplify annotation, the video was stabilized using the inverse compositional algorithm for image alignment by Baker and Matthews [15].

After video stabilization, 250,000 frames (in 137 approximately minute long segments extracted from the 10 hours of video) were annotated for a total of 350,000 bounding boxes around 2,300 unique pedestrians. To make such a large scale labeling effort feasible we created a user-friendly labeling tool, shown in Fig. 3. Its most salient aspect is an interactive procedure where the annotator labels a sparse set of frames and the system automatically predicts pedestrian positions in intermediate frames. Specifically, after an annotator labels a bounding box around the same pedestrian in at least two frames, BBs in intermediate frames are interpolated using cubic interpolation (applied independently to each coordinate of the BBs). Thereafter, every time an annotator alters a BB, BBs in all the unlabeled frames are reinterpolated. The annotator continues until satisfied with the result. We experimented with more sophisticated interpolation schemes, including relying on tracking; however, cubic interpolation proved best. Labeling the  $\sim 2.3$  hours of video, including verification, took  $\sim 400$  hours total (spread across multiple annotators).



Fig. 3. The annotation tool allows annotators to efficiently navigate and annotate a video in a minimum amount of time. Its most salient aspect is an interactive procedure where the annotator labels only a sparse set of frames and the system automatically predicts pedestrian positions in intermediate frames. The annotation tool is available on the project website.

For every frame in which a given pedestrian is visible, annotators mark a BB that indicates the full extent of the *entire* pedestrian (BB-full); for occluded pedestrians this involves estimating the location of hidden parts. In addition a second BB is used to delineate the visible region (BB-vis), see Fig. 5a. During an occlusion event, the estimated full BB stays relatively constant while the visible BB may change rapidly. For comparison, in the PASCAL labeling scheme [14] only the visible BB is labeled and occluded objects are marked as “truncated.”

Each sequence of BBs belonging to a single object was assigned one of three labels. Individual pedestrians were labeled “Person” ( $\sim 1,900$  instances). Large groups for which it would have been tedious or impossible to label individuals were delineated using a single BB and labeled as “People” ( $\sim 300$ ). In addition, the label “Person?” was assigned when clear identification of a pedestrian was ambiguous or easily mistaken ( $\sim 110$ ).

## 2.2 Data Set Statistics

A summary of the data set is given in Fig. 2b. About 50 percent of the frames have no pedestrians, while 30 percent have two or more, and pedestrians are visible for 5 s on average. Below, we analyze the distribution of pedestrian scale, occlusion, and location. This serves to establish the requirements of a real world system and to help identify constraints that can be used to improve automatic pedestrian detection systems.

### 2.2.1 Scale Statistics

We group pedestrians by their image size (height in pixels) into three scales: near (80 or more pixels), medium (between 30-80 pixels), and far (30 pixels or less). This division into three scales is motivated by the distribution of sizes in the data set, human performance, and automotive system requirements.

In Fig. 4a, we histogram the heights of the 350,000 BBs using logarithmic sized bins. The heights are roughly lognormally distributed with a median of 48 pixels and a log-average of 50 pixels (the log-average is equivalent to the geometric mean and is more representative of typical values for lognormally distributed data than the arithmetic mean,

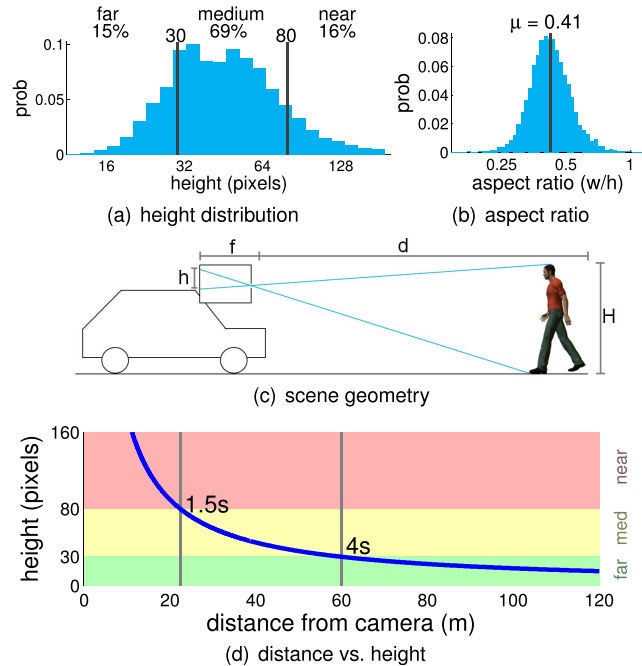


Fig. 4. (a) Distribution of pedestrian pixel heights. We define the near scale to include pedestrians over 80 pixels, the medium scale as 30-80 pixels, and the far scale as under 30 pixels. Most observed pedestrians ( $\sim 69\%$ ) are at the medium scale. (b) Distribution of BB aspect ratio; on average  $w \approx 0.41h$ . (c) Using the pinhole camera model, a pedestrian’s pixel height  $h$  is inversely proportional to distance to the camera  $d$ :  $h/f \approx H/d$ . (d) Pixel height  $h$  as a function of distance  $d$ . Assuming an urban speed of 55 km/h, an 80 pixel person is just 1.5 s away, while a 30 pixel person is 4 s away. Thus, for automotive settings, detection is most important at medium scales (see Section 2.2.1 for details).

which is 60 pixels in this case). Cutoffs for the near/far scales are marked. Note that  $\sim 69\%$  of the pedestrians lie in the medium scale, and that the cutoffs for the near/far scales correspond to about  $\pm 1$  standard deviation (in log space) from the log-average height of 50 pixels. Below 30 pixels, annotators have difficulty identifying pedestrians reliably.

Pedestrian width is likewise lognormally distributed and, moreover, so is the joint distribution of width and height (not shown). As any linear combination of the components of a multivariate normal distribution is also normally distributed, so should the BB aspect ratio be (defined as  $w/h$ ) since  $\log(w/h) = \log(w) - \log(h)$ . A histogram of the aspect ratios, using logarithmic bins, is shown in Fig. 4b, and indeed the distribution is lognormal. The log-average aspect ratio is 0.41, meaning that typically  $w \approx .41h$ . However, while BB height does not vary considerably given a constant distance to the camera, the BB width can change with the pedestrian’s pose (especially arm positions and relative angle). Thus, although we could have defined the near, medium and far scales using the width, the consistency of the height makes it better suited.

Detection in the medium scale is essential for automotive applications. We chose a camera setup that mirrors expected automotive settings:  $640 \times 480$  resolution, 27 degrees vertical field of view, and focal length fixed at 7.5 mm. The focal length in pixels is  $f \approx 1,000$  (obtained from  $480/2/f = \tan(27^\circ/2)$  or using the camera’s pixel size of  $7.5 \mu\text{m}$ ). Using a pinhole camera model (see Fig. 4c), an object’s observed



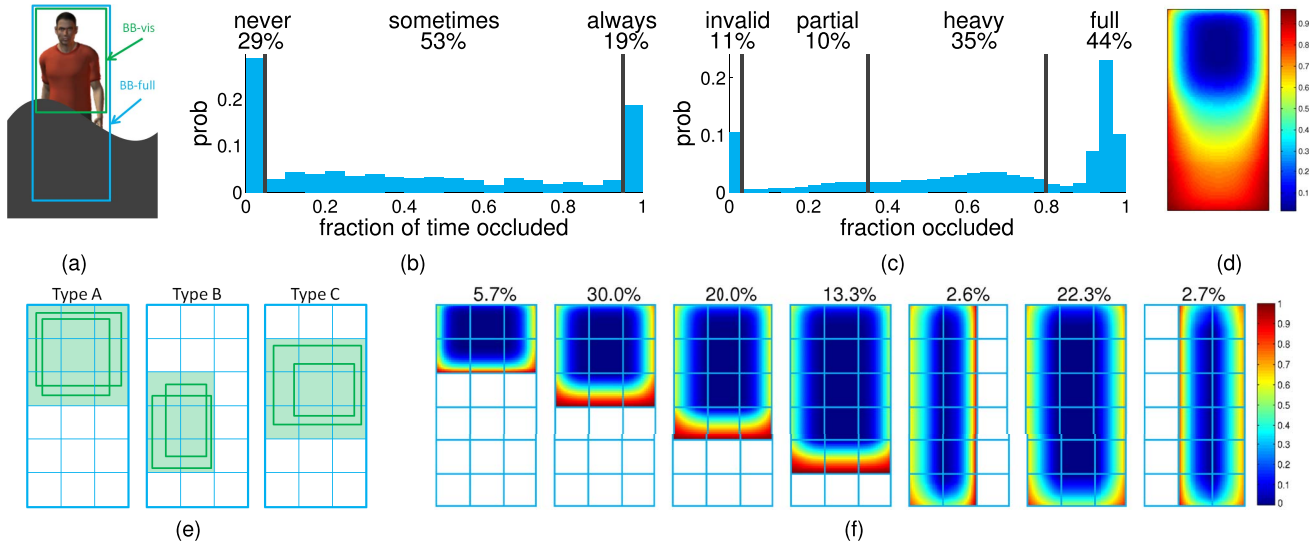


Fig. 5. Occlusion statistics. (a) For all occluded pedestrians annotators labeled both the full extent of the pedestrian (BB-full) and the visible region (BB-vis). (b) Most pedestrians (70 percent) are occluded in at least one frame, underscoring the importance of detecting occluded people. (c) Fraction of occlusion can vary significantly (0 percent occlusion indicates that a BB could not represent the extent of the visible region). (d) Occlusion is far from uniform with pedestrians typically occluded from below. (e) To observe further structure in the types of occlusions that actually occur, we quantize occlusion into a fixed number of types. (f) Over 97 percent of occluded pedestrians belong to just a small subset of the hundreds of possible occlusion types. Details in Section 2.2.2.

pixel height  $h$  is inversely proportional to the distance  $d$  to the camera:  $h \approx Hf/d$ , where  $H$  is the true object height. Assuming  $H \approx 1.8$  m tall pedestrians, we obtain  $d \approx 1,800/h$  m. With the vehicle traveling at an urban speed of 55 km/h ( $\sim 15$  m/s), an 80 pixel person is just 1.5 s away, while a 30 pixel person is 4 s away (see Fig. 4d). Thus, detecting near scale pedestrians may leave insufficient time to alert the driver, while far scale pedestrians are less relevant.

We shall use the near, medium, and far scale definitions throughout this work. Most pedestrians are observed at the medium scale and, for safety systems, detection must occur in this scale as well. Human performance is also quite good in the near and medium scales but degrades noticeably at the far scale. However, most current detectors are designed for the near scale and perform poorly even at the medium scale (see Section 5). Thus, there is an important mismatch in current research efforts and the requirements of real systems. Using higher resolution cameras would help; nevertheless, given the good human performance and lower cost, we believe that accurate detection in the medium scale is an important and reasonable goal.

### 2.2.2 Occlusion Statistics

Occluded pedestrians were annotated with two BBs that denote the visible and full pedestrian extent (see Fig. 5a). We plot frequency of occlusion in Fig. 5b, i.e., for each pedestrian we measure the fraction of frames in which the pedestrian was at least somewhat occluded. The distribution has three distinct regions: pedestrians that are never occluded (29 percent), occluded in some frames (53 percent), and occluded in all frames (19 percent). Over 70 percent of pedestrians are occluded in at least one frame, underscoring the importance of detecting occluded people. Nevertheless, little previous work has been done to quantify occlusion or detection performance in the presence of occlusion (using real data).

For each occluded pedestrian, we can compute the fraction of occlusion as 1 minus the visible pedestrian area divided by total pedestrian area (calculated from the visible and full BBs). Aggregating, we obtain the histogram in Fig. 5c. Over 80 percent occlusion typically indicates full occlusion, while 0 percent is used to indicate that a BB could not represent the extent of the visible region (e.g., due to a diagonal occluder). We further subdivide the cases in between into *partial* occlusion (1-35 percent area occluded) and *heavy* occlusion (35-80 percent occluded).

We investigated which regions of a pedestrian were most likely to be occluded. For each frame in which a pedestrian was partially to heavily occluded (1-80 percent fraction of occlusion), we created a binary  $50 \times 100$  pixel occlusion mask using the visible and full BBs. By averaging the resulting  $\sim 54$  k occlusion masks, we computed the probability of occlusion for each pixel (conditioned on the person being partially occluded); the resulting heat map is shown in Fig. 5d. Observe the strong bias for the lower portion of the pedestrian to be occluded, particularly the feet, and for the top portion, especially the head, to be visible. An intuitive explanation is that most occluding objects are supported from below as opposed to hanging from above (another but less likely possibility is that it is difficult for annotators to detect pedestrians if only the feet are visible). Overall, occlusion is far from uniform and exploiting this finding could help improve the performance of pedestrian detectors.

Not only is occlusion highly nonuniform, there is significant additional structure in the types of occlusions that actually occur. Below, we show that after quantizing occlusion masks into a large number of possible types, nearly all occluded pedestrians belong to just a handful of the resulting types. To quantize the occlusions, each BB-full is registered to a common reference BB that has been partitioned into  $q_x$  by  $q_y$  regularly spaced cells; each BB-vis can then be assigned a type according to the smallest set of



Scenarios ext0/ext1 allow for evaluation of existing, pre-trained pedestrian detectors, while cal0/cal1 involve training using the Caltech training data (S0-S5). The results reported here use the ext0/ext1 scenarios, thus allowing for a broad survey of existing pretrained pedestrian detectors. Authors are encouraged to retrain their systems on our large training set and evaluate under scenarios cal0/cal1. Authors should use ext0/cal0 during detector development, and only evaluate after finalizing all parameters under scenarios ext1/cal1.

## 2.4 Comparison of Pedestrian Data Sets

Existing data sets may be grouped into two types: 1) “person” data sets containing people in unconstrained pose in a wide range of domains and 2) “pedestrian” data sets containing upright, possibly moving people. The most widely used “person” data sets include subsets of the MIT LabelMe data [23] and the PASCAL VOC data sets [14]. In this work, we focus on pedestrian detection, which is more relevant to automotive safety.

Table 1 provides an overview of existing pedestrian data sets. The data sets are organized into three groups. The first includes older or more limited data sets. The second includes more comprehensive data sets, including the INRIA [7], ETH [4], and TUD-Brussels [5] pedestrian data sets and the Daimler detection benchmark (Daimler-DB) [6]. The final row contains information about the Caltech Pedestrian Data Set. Details follow below.

**Imaging setup.** Pedestrians can be labeled in photographs [7], [16], surveillance video [17], [24], and images taken from a mobile recording setup, such as a robot or vehicle [4], [5], [6]. Data Sets gathered from photographs suffer from *selection bias*, as photographs are often manually selected, while surveillance videos have restricted backgrounds and thus rarely serve as a basis for detection data sets. Data Sets collected by continuously filming from a mobile recording setup, such as the Caltech Pedestrian Data Set, largely eliminate selection bias (unless some scenes are staged by actors, as in [6]) while having moderately diverse scenes.

**Data set size.** The amount and type of data in each data set is given in the next six columns. The columns are: number of pedestrian windows (not counting reflections, shifts, etc.), number of images with no pedestrians (a † indicates cropped negative windows only), and number of uncropped images containing at least one pedestrian. The Caltech Pedestrian Data Set is two orders of magnitude larger than most existing data sets.

**Data set type.** Older data sets, including the MIT [16], CVC [19], and NICTA [22] pedestrian data sets and the Daimler classification benchmark (Daimler-CB) [21], tend to contain cropped pedestrian windows only. These are known as “classification” data sets as their primary use is to train and test binary classification algorithms. In contrast, data sets that contain pedestrians in their original context are known as “detection” data sets and allow for the design and testing of full-image detection systems. The Caltech data set along with all the data sets in the second set (INRIA, ETH, TUD-Brussels, and Daimler-DB) can serve as “detection” data sets.

**Pedestrian scale.** Table 1 additionally lists the 10th percentile, median, and 90th percentile pedestrian pixel heights for each data set. While the INRIA data set has fairly high-resolution pedestrians, most data sets gathered from mobile platforms have median heights that range from 50-100 pixels. This emphasizes the importance of detection of low-resolution pedestrians, especially for applications on mobile platforms.

**Data set properties.** The final columns summarize additional data set features, including the availability of color images, video data, temporal correspondence between BBs and occlusion labels, and whether “per-image” evaluation and unbiased selection criteria were used.

As mentioned, in our performance evaluation we additionally use the INRIA [7], ETH [4], TUD-Brussels [5], and Daimler-DB [6] data sets. The INRIA data set helped drive recent advances in pedestrian detection and remains one of the most widely used despite its limitations. Much like the Caltech data set, the ETH, TUD-Brussels, and Daimler-DB data sets are all captured in urban settings using a camera mounted to a vehicle (or stroller in the case of ETH). While annotated in less detail than the Caltech data set (see Table 1), each can serve as “detection” data set and is thus suitable for use in our evaluation.

We conclude by summarizing the most important and novel aspects of the Caltech Pedestrian Data Set. The data set includes  $O(10^5)$  pedestrian BBs labeled in  $O(10^5)$  frames and remains the largest such data set to date. It contains color video sequences and includes pedestrians with a large range of scales and more scene variability than typical pedestrian data sets. Finally, it is the only data set with detailed occlusion labels and one of the few to provide temporal correspondence between BBs.

## 3 EVALUATION METHODOLOGY

Proper evaluation methodology is a crucial and surprisingly tricky topic. In general, there is no single “correct” evaluation protocol. Instead, we have aimed to make our evaluation protocol quantify and rank detector performance in a realistic, unbiased, and informative manner.

To allow for exact comparisons, we have posted the evaluation code, ground truth annotations, and detection results for all detectors on all data sets on the project website. Use of the exact same evaluation code (as opposed to a reimplementations) ensures consistent and reproducible comparisons. Additionally, given all the detector outputs, practitioners can define novel performance metrics with which to reevaluate the detectors. This flexibility is important because while we make every effort to define realistic and informative protocols, performance evaluation is ultimately task dependent.

Overall, the evaluation protocol has changed substantially since our initial version described in [3], resulting in a more accurate and informative evaluation of the state of the art. We begin with an overview of full image evaluation in Section 3.1. Next, we discuss evaluation using subsets of the ground truth and detections in Sections 3.2 and 3.3, respectively. In Section 3.4, we propose and motivate standardizing BB aspect ratio. Finally, in Section 3.5, we examine the alternative per-window (PW) evaluation methodology.

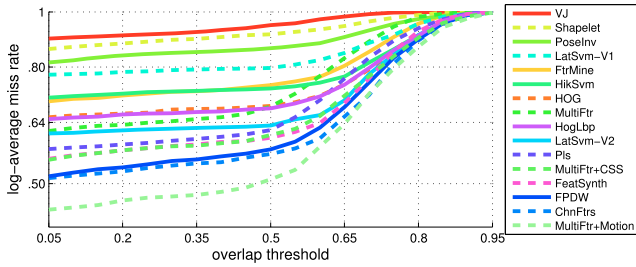


Fig. 7. Log-average miss rates for 50 pixel or taller pedestrians as a function of the threshold on overlap area (see (1)). Decreasing the threshold below 0.5 has little effect on reported performance. However, increasing it over  $\sim 0.6$  results in rapidly increasing log-average miss rates as improved localization accuracy is necessary.

### 3.1 Full Image Evaluation

We perform single frame evaluation using a modified version of the scheme laid out in the PASCAL object detection challenges [14]. A detection system needs to take an image and return a BB and a score or confidence for each detection. The system should perform multiscale detection and any necessary nonmaximal suppression (NMS) for merging nearby detections. Evaluation is performed on the final output: the list of detected BBs.

A detected BB ( $BB_{dt}$ ) and a ground truth BB ( $BB_{gt}$ ) form a potential match if they overlap sufficiently. Specifically, we employ the PASCAL measure, which states that their area of overlap must exceed 50 percent:

$$a_o \doteq \frac{\text{area}(BB_{dt} \cap BB_{gt})}{\text{area}(BB_{dt} \cup BB_{gt})} > 0.5. \quad (1)$$

The evaluation is insensitive to the exact threshold as long as it is below about 0.6, see Fig. 7. For larger values performance degrades rapidly as improved localization accuracy is necessary; thus, to focus on detection accuracy, we use the standard threshold of 0.5 throughout.

Each  $BB_{dt}$  and  $BB_{gt}$  may be matched at most once. We resolve any assignment ambiguity by performing the matching greedily. Detections with the highest confidence are matched first; if a detected BB matches multiple ground truth BBs, the match with highest overlap is used (ties are broken arbitrarily). In rare cases this assignment may be suboptimal, e.g., in crowded scenes [25], but in practice the effect is minor. Unmatched  $BB_{dt}$  count as false positives and unmatched  $BB_{gt}$  as false negatives.

To compare detectors we plot miss rate against false positives per image (FPPI) (using log-log plots) by varying the threshold on detection confidence (e.g., see Figs. 11 and 13). This is preferred to precision recall curves for certain tasks, e.g., automotive applications, as typically there is an upper limit on the acceptable false positives per image rate independent of pedestrian density.

We use the *log-average miss rate* to summarize detector performance, computed by averaging miss rate at nine FPPI rates evenly spaced in log-space in the range  $10^{-2}$  to  $10^0$  (for curves that end before reaching a given FPPI rate, the minimum miss rate achieved is used). Conceptually, the log-average miss rate is similar to the *average precision* [26] reported for the PASCAL challenge [14] in that it represents the entire curve by a single reference value. As curves are somewhat linear in this range (e.g., see Fig. 13),

the log-average miss rate is similar to the performance at  $10^{-1}$  FPPI but in general gives a more stable and informative assessment of performance. A similar performance measure was used in [27].

We conclude by listing additional details. Some detectors output BBs with padding around the pedestrian (e.g., HOG outputs  $128 \times 64$  BBs around 96 pixel tall people), such padding is cropped (see also Section 3.4). Methods usually detect pedestrians at some minimum size; to coax smaller detections, we upscale the input images. For ground truth, the full BB is always used for matching, not the visible BB, even for partially occluded pedestrians. Finally, all reported results on the Caltech data set are computed using every 30th frame (starting with the 30th frame) due to the high-computational demands of some of the detectors evaluated (see Fig. 15).

### 3.2 Filtering Ground Truth

Often we wish to exclude portions of a data set during evaluation. This serves two purposes: 1) excluding ambiguous regions, e.g., crowds annotated as “People” where the locations of individuals is unknown, and 2) evaluating performance on various subsets of a data set, e.g., on pedestrians in a given scale range. However, we cannot simply discard a subset of ground truth labels as this would cause overreporting of false positives.

Instead, to exclude portions of a data set, we introduce the notion of *ignore* regions. Ground truth BBs selected to be ignored, denoted using  $BB_{ig}$ , need not be matched; however, matches are not considered mistakes either. For example, to evaluate performance on unoccluded pedestrians, we set all occluded pedestrian BBs to ignore. Evaluation is purposely lenient: Multiple detections can match a single  $BB_{ig}$ ; moreover, a detection may match any *subregion* of a  $BB_{ig}$ . This is useful when the number or location of pedestrians within a single  $BB_{ig}$  is unknown as in the case of groups labeled as “People.”

In the proposed criterion, a  $BB_{dt}$  can match any subregion of a  $BB_{ig}$ . The subregion that maximizes area of overlap (1) with  $BB_{dt}$  is  $BB_{dt} \cap BB_{ig}$ , and the resulting maximum area of overlap is

$$a_o \doteq \frac{\text{area}(BB_{dt} \cap BB_{ig})}{\text{area}(BB_{dt})}. \quad (2)$$

Matching proceeds as before, except  $BB_{dt}$  matched to  $BB_{ig}$  do *not* count as true positives and unmatched  $BB_{ig}$  do *not* count as false negatives. Matches to  $BB_{gt}$  are preferred, meaning a  $BB_{dt}$  can only match a  $BB_{ig}$  if it does not match any  $BB_{gt}$ , and multiple matches to a single  $BB_{ig}$  are allowed.

As discussed, setting a  $BB_{gt}$  to ignore is not the same as discarding it; in the latter case detections in the ignore regions would count as false positives. Four types of BBs are always set to ignore: any BB under 20 pixels high or truncated by image boundaries, containing a “Person?” (ambiguous cases), or containing “People.” Detections within these regions do not affect performance.

### 3.3 Filtering Detections

In order to evaluate on only a subset of the data set, we must filter detector responses outside the considered evaluation range (in addition to filtering ground truth labels). For example, when evaluating performance in a



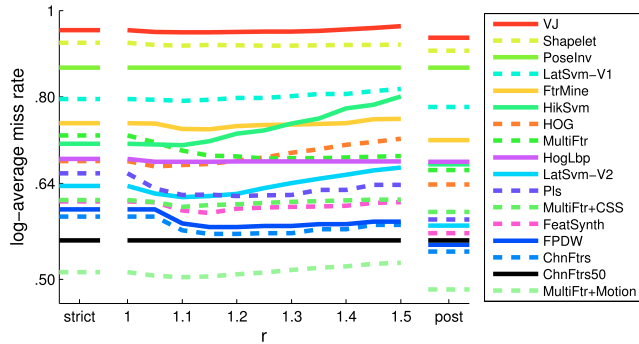


Fig. 8. Comparison of detection filtering strategies used for evaluating performance in a fixed range of scales. Left: Strict filtering, used in our previous work [3], undercounts true positives, thus underreporting results. Right: Postfiltering undercounts false positives, thus overreporting results. Middle: Expanded filtering as a function of  $r$ . Expanded filtering with  $r = 1.25$  offers a good compromise between strict and postfiltering for measuring both true and false positives accurately.

fixed scale range, detections far outside the scale range under consideration should not influence the evaluation.

The filtering strategy used in our previous work [3] was too stringent and resulted in underreporting of detector performance (this was also independently observed by Walk et al. [28]). Here, we consider three possible filtering strategies, *strict filtering* (used in our previous work), *postfiltering*, and *expanded filtering*, that we believe most accurately reflects true performance. In all cases, matches to  $BB_{gt}$  outside the selected evaluation range neither count as true or false positives.

**Strict filtering.** All detections outside the selected range are removed *prior* to matching. If a  $BB_{gt}$  inside the range was matched only by a  $BB_{dt}$  outside the range, then after strict filtering it would become a false negative. Thus, performance is underreported.

**Postfiltering.** Detections outside the selected evaluation range are allowed to match  $BB_{gt}$  inside the range. After matching, any unmatched  $BB_{dt}$  outside the range is removed and does *not* count as a false positive. Thus, performance is overreported.

**Expanded filtering.** Similar to strict filtering, except all detections outside an *expanded* evaluation range are removed prior to evaluation. For example, when evaluating in a scale range from  $S_0$  to  $S_1$  pixels, all detections outside a range  $S_0/r$  to  $S_1r$  are removed. This can result in slightly more false positives than postfiltering, but also fewer missed detections than strict filtering.

Fig. 8 shows the log-average miss rate on 50 pixel and taller pedestrians under the three filtering strategies (see Section 4 for detector details) and for various choices of  $r$  (for expanded filtering). Expanded filtering offers a good compromise<sup>1</sup> between strict filtering (which underreports

1. Additionally, strict and post filtering are flawed as they can be easily exploited (either purposefully or inadvertently). Under post filtering, generating large numbers of detections just outside the evaluation range can increase detection rate. Under strict filtering, running a detector in the exact evaluation range ensures all detections fall within that range which can also artificially increase detection rate. To demonstrate the latter exploit, in Fig. 8 we plot the performance of CHNFTRS50, which is CHNFTRS [29] applied to detect pedestrians over 50 pixels. Its performance is identical under each strategy; however, its relative performance is significantly inflated under strict filtering. Expanded filtering cannot be exploited in either manner.

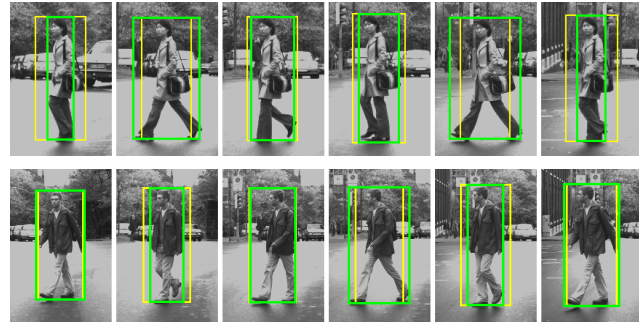


Fig. 9. Standardizing aspect ratios. Shown are profile views of two pedestrians. The original annotations are displayed in green (best viewed in color); these were used to crop fixed size windows centered on each pedestrian. Observe that while BB height changes gradually, BB width oscillates significantly as it depends on the positions of the limbs. To remove any effect *pose* may have on the evaluation of *detection*, during benchmarking width is standardized to be a fixed fraction of the height (see Section 3.4). The resulting BBs are shown in yellow.

performance) and postfiltering (which overreports performance). Moreover, detector ranking is robust to the exact value of  $r$ . Thus, throughout this work, we use expanded filtering (with  $r = 1.25$ ).

### 3.4 Standardizing Aspect Ratios

Significant variability in both ground truth and detector BB width can have an undesirable effect on evaluation. We discuss the sources of this variability and propose to standardize aspect ratio of both the ground truth and detected BBs to a fixed value. Doing so removes an extraneous and arbitrary choice from detector design and facilitates performance comparisons.

The height of annotated pedestrians is an accurate reflection of their scale while the width also depends on *pose*. Shown in Fig. 9 are consecutive, independently annotated frames from the Daimler detection benchmark [6]. Observe that while BB height changes gradually, the width oscillates substantially. BB height depends on a person's actual height and distance from the camera, but the width additionally depends on the positions of the limbs, especially in profile views. Moreover, the typical width of annotated BBs tends to vary across data sets. For example, although the log-mean aspect ratio (see Section 2.2.1) in the Caltech and Daimler data sets is 0.41 and 0.38, respectively, in the INRIA data set [7] it is just 0.33 (possibly due to the predominance of stationary people).

Various detectors likewise return different width BBs. The aspect ratio of detections ranges from a narrow 0.34 for PLS to a wide 0.5 for MULTIFTR, while LATSVM attempts to estimate the width (see Section 4 for detector references). For older detectors that output uncropped BBs, we must choose the target width ourselves. In general, a detector's aspect ratio depends on the data set used during development and is often chosen after training.

To summarize, the width of both ground truth and detected BBs is more variable and arbitrary than the height. To remove any effects this may have on performance evaluation, we propose to standardize all BBs to an aspect ratio of 0.41 (the log-mean aspect ratio in the Caltech data set). We keep BB height and center fixed while adjusting the



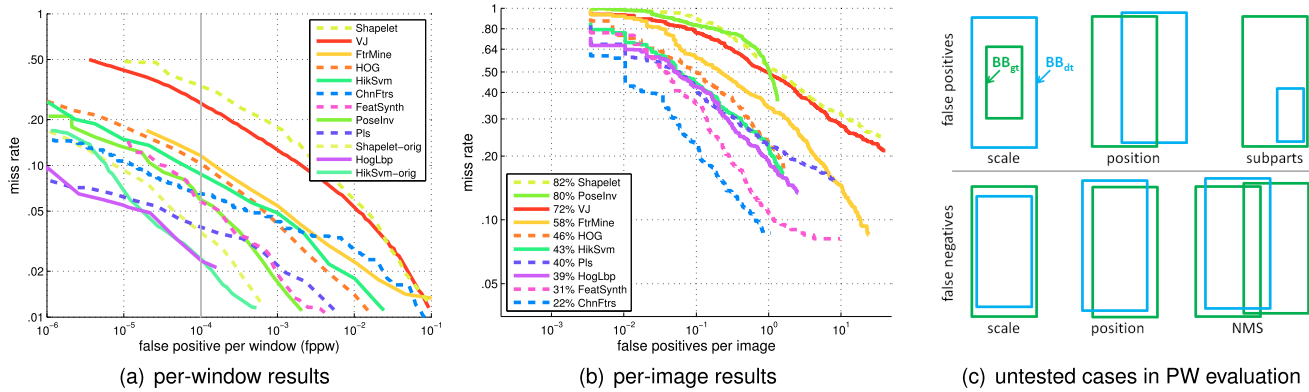


Fig. 10. Per-window versus full image evaluation on the INRIA pedestrian data set (see Section 4 for detector details and Section 5.2 for complete results). Legends are ordered by performance. (a) PW results reproduced from their original publications. (b) Full image results obtained by evaluating on the same pedestrians but within their original image context. While PW and full image performance are somewhat correlated, the ranking of competing methods is substantially different. (c) Illustration of six cases not tested during PW evaluation that can give rise to false positives (top) or false negatives (bottom) in full image evaluation. False positives can arise from detections on body parts or at incorrect scales or positions, while false negatives can arise from slight misalignments between the tested windows and true pedestrian locations or from NMS.

width (see Fig. 9). Note that the ETH [4] and TUD-Brussels [5] evaluation protocols also suggested standardizing the aspect ratio, although to an arbitrarily chosen constant of 0.5. In general, the exact constant has only a minor effect on reported performance; however, it is important that detector and ground truth aspect ratios match. For example, standardizing the aspect ratios had a large positive effect on detectors that return narrow BBs (including PLS and LATSVM-V2). All results reported in this paper use the standardized aspect ratios.

### 3.5 Per-Window versus Full Image Evaluation

An alternative methodology for evaluating detectors based on *binary classifiers* is to measure their *per-window* performance on cropped positive and negative image windows, thus isolating classifier performance from the overall detection system. PW evaluation is commonly used to compare classifiers (as opposed to detectors) or to evaluate systems that perform automatic region of interest (ROI) generation [30]. Note that not all detectors are based on classifiers (e.g., [31], [32]); such detectors cannot be evaluated using PW metrics.

A common assumption is that better PW performance leads to better detection performance. In practice, we find that PW and full image performance are only weakly correlated, see Fig. 10. The PW results are reproduced from their original publications<sup>2</sup> (except the VJ curve, which is reproduced from [7]); the full image results were obtained by evaluating on the same pedestrians but within their original image context. While PW and full image performance are somewhat correlated, the ranking of competing methods is substantially different.

There are a number of reasons for this discrepancy. Choices made in converting a binary classifier to a detector,

2. PW evaluation must be performed with care: Cropped positive and negative windows obtained by different sampling procedures may contain window boundary effects that classifiers can exploit as discriminative features, leading to overfitting. We observed this for the SHAPELET [33] and HIKSVM [34] detectors, see also [www.cs.sfu.ca/~mori/research/papers/sabzmezdani\\_shapelet\\_cvpr07.html](http://www.cs.sfu.ca/~mori/research/papers/sabzmezdani_shapelet_cvpr07.html) and <http://www.cs.berkeley.edu/~smaji/projects/ped-detector/>. The original (ORIG) and corrected PW results are shown in Fig. 10a; in both cases the overfitting was discovered only after full image evaluation.

including choices for spatial and scale stride and non-maximal suppression, influence full image performance. Moreover, the windows tested during PW evaluation are typically not the same as the windows tested during full image detection, see Fig. 10c.

Full image metrics provide a natural measure of error of an overall detection system, and in this work we use full image metrics throughout. While the PW methodology is useful for isolating evaluation of binary classifiers (the classification task), ultimately the goal of pedestrian detection is to output the location of all pedestrians in an image (the detection task), and for this task full image metrics are appropriate. We thus advocate using full image metrics for evaluation of pedestrian detection as is standard for general object detection [14].

## 4 DETECTION ALGORITHMS

We focus on computer vision algorithms for detecting pedestrians in individual monocular images, which we refer to simply as “pedestrian detectors.” We begin with an overview of pedestrian detectors in Section 4.1, examining the ideas introduced in detection in the last decade. In Section 4.2, we enumerate and discuss in detail the 16 representative state-of-the-art detectors used in our evaluation.

### 4.1 Survey of the State of the Art

We review pedestrian detectors with a focus on sliding window approaches. These appear most promising for low to medium resolution settings, under which segmentation [35] or keypoint [36], [37] based methods often fail. We list abbreviations of detectors used in our evaluation in brackets [ALG]. For an overview of how detectors are incorporated into full automotive systems that utilize stereo, scene geometry, tracking, or other imaging modalities (e.g., [30], [38], [39], [40], [41]), we refer readers to [2], [42], [43]. In this work, we focus on the detectors themselves.

Papageorgiou and Poggio [16] proposed one of the first sliding window detectors, applying support vector machines (SVM) to an overcomplete dictionary of multiscale Haar

wavelets. Viola and Jones [VJ] [44] built upon these ideas, introducing integral images for fast feature computation and a cascade structure for efficient detection, and utilizing AdaBoost for automatic feature selection. These ideas continue to serve as a foundation for modern detectors.

Large gains came with the adoption of gradient-based features. Inspired by SIFT [45], Dalal and Triggs [HOG] [7] popularized histogram of oriented gradient (HOG) features for detection by showing substantial gains over intensity-based features. Zhu et al. [46] sped up HOG features by using integral histograms [47]. In earlier work, Shashua et al. [48] proposed a similar representation for characterizing spatially localized parts for modeling pedestrians. Since their introduction, the number of variants of HOG features has proliferated greatly with nearly all modern detectors utilizing them in some form.

Shape features are also a frequent cue for detection. Gavrilu and Philomin [49], [50] employed the Hausdorff distance transform and a template hierarchy to rapidly match image edges to a set of shape templates. Wu and Nevatia [17] utilized a large pool of short line and curve segments, called “edgelet” features, to represent shape locally. Boosting was used to learn head, torso, leg, and full body detectors; this approach was extended in [18] to handle multiple viewpoints. Similarly, “shapelets” [33] are shape descriptors discriminatively learned from gradients in local patches; boosting was used to combine multiple shapelets into an overall detector [SHAPELET]. Liu et al. [51] proposed “granularity-tunable” features that allow for representations with levels of uncertainty ranging from edgelet to HOG type features; an extension to the spatiotemporal domain was developed in [52].

Motion is another important cue for human perception; nevertheless, successfully incorporating motion features into detectors has proven challenging given a moving camera. Given a static camera, Viola et al. [53] proposed computing Haar-like features on difference images, resulting in large performance gains. For nonstatic imaging setups, however, camera motion must be factored out. Dalal et al. [54] modeled motion statistics based on an optical flow field’s internal differences, thereby compensating for uniform image motion locally. While the features were successful on a per-window basis [54], for full image detection the benefit appeared minimal [55]. This was resolved by Wojek et al. [5], who showed that certain modifications were necessary to make the motion features effective for detection.

While no single feature has been shown to outperform HOG, additional features can provide complementary information. Wojek and Schiele [MULTIFTR] [56] showed how a combination of Haar-like features, shapelets [33], shape context [57] and HOG features outperforms any individual feature. Walk et al. [28] extended this framework by additionally combining local color self-similarity [MULTIFTR+CSS] and the motion features discussed above [MULTIFTR+MOTION]. Likewise, Wu and Nevatia [58] automatically combined HOG, edgelet, and covariance features. Wang et al. [59] combined a texture descriptor based on local binary patterns (LBP) [60] with HOG [HOG+LBP]; additionally, a linear SVM classifier was modified to perform basic occlusion reasoning. In addition

to HOG and LBP, [61] used local ternary patterns (variants of LBP). Color information and implicit segmentation were added in [62], with a performance improvement over pure HOG.

Dollár et al. [29] proposed an extension of [VJ] where Haar-like feature are computed over multiple channels of visual data [CHNFTRS], including LUV color channels, grayscale, gradient magnitude, and gradient magnitude quantized by orientation (implicitly computing gradient histograms), providing a simple and uniform framework for integrating multiple feature types. In the “Fastest Pedestrian Detector in the West” [FPDW] [63], this approach was extended to fast multiscale detection after it was demonstrated how features computed at a single scale can be used to approximate feature at nearby scales.

Considerable effort has also been devoted to improving the learning framework. Tuzel et al. [64] utilized covariance matrices computed locally over various features as object descriptors. Since covariance matrices do not lie on a vector space, the boosting framework was modified to work on Riemannian manifolds, with improved performance. Maji et al. [34] proposed an approximation to the histogram intersection kernel for use with SVMs [HIKSVM], allowing for substantial speedups and thus enabling a nonlinear SVM to be used in sliding-window detection. Babenko et al. [65] proposed an approach for simultaneously separating data into coherent groups and training separate classifiers for each; Wojek et al. [5] showed that both Maji et al. [34] and Babenko et al. [65] gave modest gains over linear SVMs and AdaBoost for pedestrian detection, especially when used in combination [66].

A number of groups have attempted to efficiently utilize very large feature spaces. “Feature mining” was proposed by Dollár et al. [67] to explore vast (possibly infinite) feature spaces using various strategies including steepest descent search prior to training a boosted classifier [FTRMINE]. These ideas were developed further by Bar-Hillel et al. [68], who introduced a scheme for synthesizing and combining a rich family of part-based features in an SVM framework [FEATSYNTH]. Schwartz et al. [69] represented pedestrians by edges, texture, and color and applied partial least squares to project the features down to a lower dimensional space prior to SVM training [PLS].

To cope with articulation, the notion of parts and pose has been investigated by several authors. Mohan et al. [73] successfully extended [16] with a two stage approach: First, head, arm, and leg detectors were trained in a fully supervised manner, next the detectors’ output was combined to fit a rough geometric model. Such fully supervised two stage approaches have been revisited over time [17], [74], [75]. Likewise, Bourdev and Malik [76] proposed to learn an exhaustive dictionary of “poselets:” parts clustered jointly in appearance and pose. Supervised pose estimation has been used in a similar manner. Lin and Davis [70] used a part-template tree to model a pedestrian’s shape locally for the head, upper body, and legs, and extracted HOG appearance descriptors along the shape’s outline [POSEINV]. Enzweiler and Gavrilu [77] labeled pedestrians as belonging to one of four canonical orientations and jointly perform classification and orientation estimation. Joint body pose estimation and

TABLE 2  
Comparison of Evaluated Pedestrian Detectors (See Section 4.2 for Details)

		Features						Learning			Detection Details				Implementation					
		gradient hist.	gradients	grayscale	color	texture	self-similarity	motion	classifier	feature learn.	part based	non-maximum suppression	model height (in pixels)	scales per octave	frames per second (fps)	log-average miss rate	training data	original code	full image evaluation	publication
VJ	[44]			✓				AdaBoost			MS	96	~14	.447	95%	INRIA				'04
SHAPELET	[33]		✓					AdaBoost	✓		MS	96	~14	.051	91%	INRIA				'07
POSEINV	[70]	✓						AdaBoost			MS	96	~18	.474	86%	INRIA	✓			'08
LATSVM-V1	[71]	✓						latent SVM	✓	✓	PM	80	10	.392	80%	PASCAL	✓	✓		'08
FTRMINE	[67]	✓	✓	✓	✓			AdaBoost	✓		PM	100	4	.080	74%	INRIA	✓			'07
HIKSVM	[34]	✓	✓					HIK SVM			MS	96	8	.185	73%	INRIA	✓			'08
HOG	[7]	✓						linear SVM			MS	96	~14	.239	68%	INRIA	✓			'05
MULTIFTR	[56]	✓		✓				AdaBoost			MS	96	~14	.072	68%	INRIA	✓	✓		'08
HOGLBP	[59]	✓				✓		linear SVM			MS	96	14	.062	68%	INRIA	✓	✓		'09
LATSVM-V2	[72]	✓						latent SVM	✓	✓	PM	96	10	.629	63%	INRIA	✓	✓		'09
PLS	[69]	✓			✓	✓		PLS+QDA	✓		PM*	96	~10	.018	62%	INRIA	✓	✓		'09
MULTIFTR+CSS	[28]	✓					✓	linear SVM			MS	96	~14	.027	61%	TUD-MP	✓	✓		'10
FEATSYNTH	[68]	✓				✓		linear SVM	✓	✓	-	96	-	-	60%	INRIA	✓	✓		'10
FPDW	[63]	✓	✓	✓	✓			AdaBoost			PM*	100	10	6.492	57%	INRIA	✓	✓		'10
CHNFTRS	[29]	✓	✓	✓	✓			AdaBoost			PM*	100	10	1.183	56%	INRIA	✓	✓		'09
MULTIFTR+MOTION	[28]	✓				✓	✓	linear SVM			MS	96	~14	.020	51%	TUD-MP	✓	✓		'10

person classification can also be formulated as a structured learning problem [78].

Notable early approaches for unsupervised part learning, including the constellation model [79], [80] and the sparse representation approach of Agarwal and Roth [81], relied on keypoints. Leibe et al. [36] adapted the implicit shape model, also based on keypoints, for detecting pedestrians. However, as few interest points are detected at lower resolutions, unsupervised part-based approaches that do not rely on keypoints have been proposed. Multiple instance learning (MIL) has been employed in order to automatically determine the position of parts without part-level supervision [82], [83]. And, in one of the most successful approaches for general object detection to date, Felzenszwalb et al. [71], [72] proposed a discriminative part-based approach that models unknown part positions as latent variables in an SVM framework [LATSVM]. As part models seem to be most successful at higher resolutions, Park et al. [84] extended this to a multiresolution model that automatically switches to parts only at sufficiently high resolutions.

## 4.2 Evaluated Detectors

We chose 16 representative state-of-the-art pedestrian detectors for this evaluation (see Section 4.1 and Table 2). Our goal was to choose a diverse set of detectors that were both representative of various lines of research and most promising in terms of originally reported performance. While we could not be exhaustive due to unavailability of many detectors and practical time and space constrains, we do believe that the selected detectors give an accurate portrait of the state of the art.

In nearly all cases, we obtained *pretrained* detectors directly from the authors as our goal was to have an unbiased evaluation of existing approaches. Any major differences from the original publications are discussed below. We thank the authors for either publishing their code online or making it available upon request.

While research in pedestrian detection is quite diverse, the approaches with the highest reported performance share many elements. These detectors typically follow a sliding window paradigm which entails feature extraction, binary classification, and dense multiscale scanning of detection windows followed by nonmaximum suppression. Below we discuss each component of the evaluated detectors, including the features, learning framework, and detection details, and conclude with implementation notes; for additional details, we refer readers to the original publications. Table 2, ordered by descending log-average miss rate on clearly visible pedestrians in the Caltech data set (see Section 5 for details), gives an overview of each detector.

**Features.** The first columns in Table 2 indicate the feature types used by each detector (specified by the general category of image content extracted and not the particular instantiation). Nearly all modern detectors employ some form of gradient histograms [7]. In addition, detectors can utilize gradients directly, as well as grayscale (e.g., Haar wavelets [44]), color, texture (including LBP [60] and co-occurrence [85]), self-similarity [86], and motion [54] features. The best performing detectors tend to use a combination of cues.

**Learning.** The second set of columns provides details about the learning paradigm used by each detector. Support vector machines [16] and boosting [44] are the most popular choices due to their theoretical guarantees, extensibility, and good performance. Boosted classifiers and linear SVMs are particularly well suited due to their speed; nonlinear kernels are less common, the exception being the fast histogram intersection kernel [34]. Boosting automatically performs feature selection; alternatively, some detectors (indicated with a mark in the “feature learning” column) learn a smaller or intermediate set of features prior to or jointly with classifier training. Finally, a few detectors, including LATSVM and FEATSYNTH, are part based.

**Detection details.** The next columns describe the detection scheme. Two dominant nonmaximum suppression approaches have emerged: mean shift (MS) mode



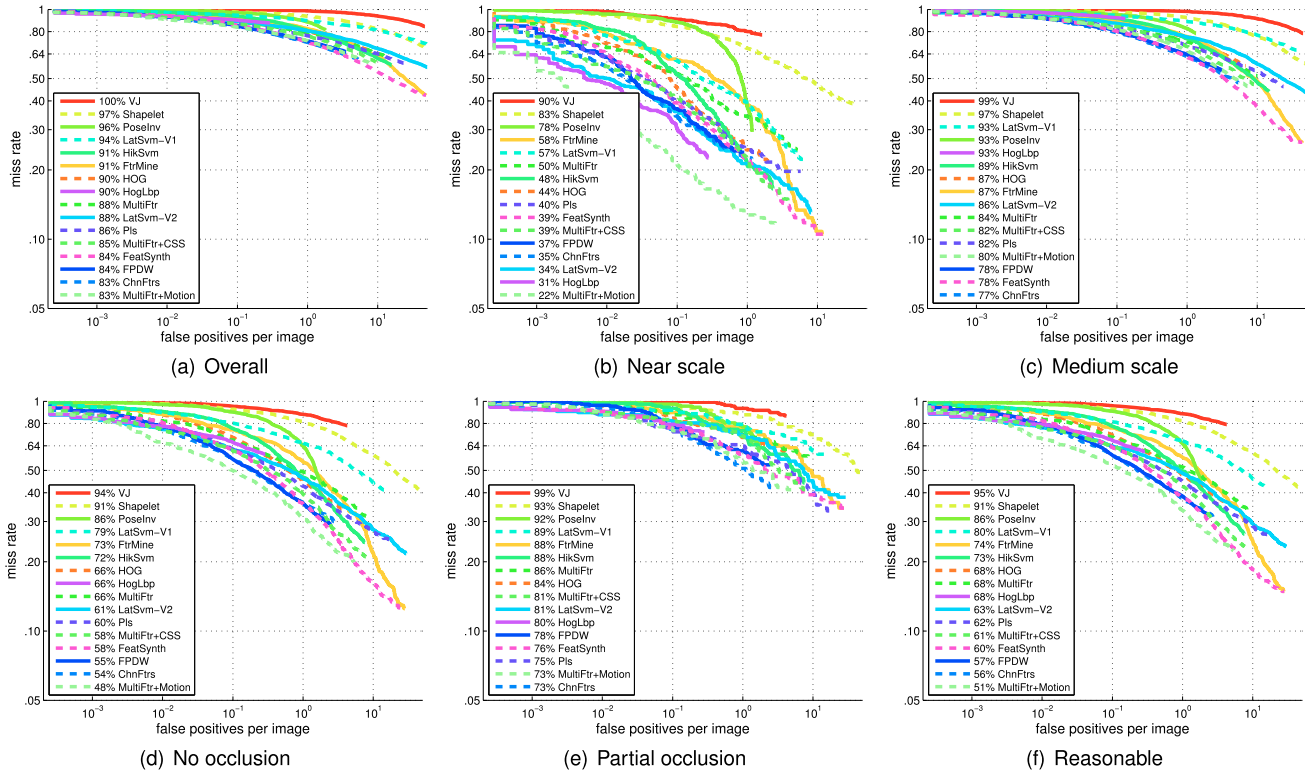


Fig. 11. Evaluation results under six different conditions on the Caltech Pedestrian Data Set. (a) Overall performance on all annotated pedestrians is unsatisfactory. (b) Performance on unoccluded pedestrians over 80 pixels tall is substantially better, but (c) degrades for 30-80 pixel pedestrians. (d) Likewise, performance on unoccluded pedestrians over 50 pixels tall is better than overall performance, but (e) degrades in the presence of partial occlusion. (f) This motivates us to evaluate performance on pedestrians at least 50 pixels tall under no or partial occlusion; we refer to this as the *reasonable* evaluation setting and use it throughout.

estimation [55] and pairwise max (PM) suppression [71], which discards the less confident of every pair of detections that overlap sufficiently according to (1). PM requires only a single parameter; in addition, a variant has been proposed (PM\*) that allows a detection to match any subregion of another detection, resulting in improved performance (see (2) and addendum to [29]). FEATSYNTH only tests windows returned by FTRMINE and does not require NMS. Pedestrian model height is typically around 96-100 pixels (the size of precropped pedestrians in the INRIA data set), with an additional 28-32 pixels of padding. For multiscale detection, usually around 10-14 scales per octave are scanned (with corresponding scale strides of 1.07-1.05); a fast multiscale scheme is proposed in [63]. Runtimes (for detecting over 100 pixel pedestrians in  $640 \times 480$  images) and log-average miss rates (on clearly visible pedestrians) are discussed in Section 5.

**Implementation notes.** The final columns of Table 2 list additional details. Most of the evaluated detectors were trained on the INRIA data set [7]; two were trained on TUD motion pairs (TUD-MP) (the training set for TUD-Brussels [5]). LATSVM-V1 was trained on Pascal [14]; LATSVM-V2 used INRIA and a later version of the latent SVM framework [72]. In nearly all cases, we used code obtained directly from the authors, the only exceptions being VJ and SHAPELET, which were reimplemented in [56]. In a few cases, the evaluated code differed from the published version: SHAPELET and HIKSVM have been corrected so they no longer overfit to boundary effects; we evaluate a variant of POSEINV based on boosting (which in our tests outperformed the much slower kernel SVM version); PLS

switched to PM\* NMS; and finally, the posted code for HOGLBP does not include occlusion reasoning (the improvement from occlusion reasoning was slight [59]).

## 5 PERFORMANCE EVALUATION

We performed an extensive evaluation of the 16 pedestrian detectors enumerated in Table 2 under various scenarios and for multiple data sets. First, in Section 5.1 we evaluate performance under different conditions using the Caltech Data Set. Next, we report performance on six additional data sets in Section 5.2 and analyze statistical significance in Section 5.3. Finally, in Section 5.4 we report runtimes.

We chose to evaluate *pretrained* detectors, obtained directly from their authors. This is an important methodological point: We assume that authors know best how to tune their algorithms; attempting to train the detectors ourselves would have opened the difficult subject of parameter tuning, making our study unwieldy. Moreover, few authors share training code; thus, insisting on retraining would have severely limited our ability to conduct a broad evaluation. Fortunately, most of the detectors were trained on the same data set (see Table 2), making them directly comparable. Additionally, testing these pretrained detectors on multiple other data sets allows us to study cross-data set generalization, a topic of crucial real-world importance.

### 5.1 Performance on the Caltech Data Set

We first analyze performance under six conditions on the testing data in the Caltech Pedestrian Data Set. Fig. 11

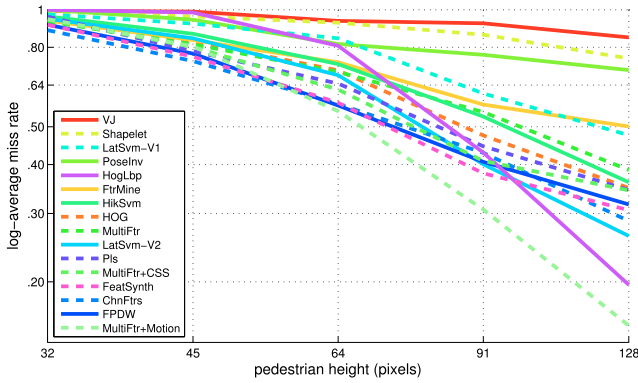


Fig. 12. Performance as a function of scale. All detectors improve rapidly with increasing scale, especially MULTIFTR+MOTION, HOGGBP, and LATSVM-V2, which utilize motion, texture, and parts, respectively. At small scales, state-of-the-art performance has considerable room for improvement.

shows performance for the overall data set, on near and medium scales, under no and partial occlusion, and on clearly visible pedestrians. We plot miss rate versus false positives per image (lower curves indicate better performance) and use log-average miss rate as a common reference value for summarizing performance. Legend entries display and are ordered by log-average miss rate from worst to best. We discuss the plots in detail below.

**Overall.** Fig. 11a plots performance on the entire test set. MULTIFTR+MOTION slightly outperforms the other detectors, with CHNFTRS a close second. However, absolute performance is poor, with a log-average miss rate of over 80 percent. To understand where the detectors fail, we examine performance under various conditions.

**Scale.** Results for near and medium scale unoccluded pedestrians, corresponding to heights of at least 80 pixels and 30-80 pixels, respectively (see Section 2.2.1), are shown in Figs. 11b and 11c. For the near scale, MULTIFTR+MOTION performs best with a log-average miss rate of only 22 percent; numerous other detectors still achieve reasonable log-average miss rates around 30-40 percent. On the medium scale, which contains over 68 percent of ground truth pedestrians (see Fig. 4a), performance degrades dramatically. CHNFTRS, FPDW, and FEATSYNTH achieve the best relative performance, but absolute performance is quite poor with 77-78 percent log-average miss rate. Moreover, the top three performing detectors on near scale pedestrians degrade most. We can see this trend clearly by plotting log-average miss rate as a function of scale. Fig. 12 shows performance at five scales between 32 and 128 pixels (see also Sections 3.2 and 3.3). Performance improves for all methods with increasing scale, but most for MULTIFTR+MOTION, HOGGBP, and LATSVM-V2. These utilize motion, texture, and parts, respectively, for which high resolutions appear to be particularly important.

**Occlusion.** The impact of occlusion on detecting 50 pixel or taller pedestrians is shown in Figs. 11d and 11e. As discussed in Section 2.2.2, we classify pedestrians as unoccluded, *partially* occluded (1-35 percent occluded), and *heavily* occluded (35-80 percent occluded). Performance drops significantly even under partial occlusion, leading to a log-average miss rate of 73 percent for CHNFTRS and

MULTIFTR+MOTION. Surprisingly, performance of part-based detectors degrades as severely as for holistic detectors.

**Reasonable.** Performance for medium scale or partially occluded pedestrians is poor, while for far scales or under heavy occlusion it is abysmal (see Fig. 16). This motivates us to evaluate performance on pedestrians over 50 pixels tall under no or partial occlusion (these are clearly visible without much context). We refer to this as the *reasonable* evaluation setting. Results are shown in Fig. 11f; MULTIFTR+MOTION, CHNFTRS, and FPDW perform best with log-average miss rates of 51-57 percent. We believe this evaluation is more representative than overall performance on all pedestrians and we use it for reporting results on all additional data sets in Section 5.2 and for the statistical significance analysis in Section 5.3.

**Localization.** Recall that the evaluation is insensitive to the exact overlap threshold used for matching so long as it is below  $\sim 0.6$  (see Section 3.1 and Fig. 7). This implies that nearly all detections that overlap the ground truth overlap it by at least half. However, as the threshold is further increased and higher localization accuracy is required, performance of all detectors degrades rapidly. Detector ranking is mostly maintained except MULTIFTR and PLS degrade more; this implies that all but these two detectors have roughly the same localization accuracy.

## 5.2 Evaluation on Multiple Data Sets

To increase the scope of our analysis, we benchmarked the detectors on six additional pedestrian detection data sets, including INRIA [7], TUD-Brussels [5], ETH [4], Daimler-DB [6], Caltech-Training, and Caltech-Japan. These data sets are discussed in Section 2.4 and Table 1; we also review their most salient aspects below. Evaluating across multiple data sets allows us to draw conclusion both about the detectors and the data sets. Here, we focus on the data sets, we return to assessing detector performance using multiple data sets in Section 5.3. Performance results for every data set are shown in Fig. 13.

We begin with a brief review of the six data sets. INRIA contains images of high-resolution pedestrians collected mostly from holiday photos (we use only the 288 test images that contain pedestrians; note that a few have incomplete labels). The remaining data sets were recorded with a moving camera in urban environments and all contain color except Daimler-DB. ETH has higher density and larger scale pedestrians than the remaining data sets (we use the refined annotations published in [5]). Caltech-Training refers to the training portion of the Caltech Pedestrian Data Set. Caltech-Japan refers to a data set we gathered in Japan that is essentially identical in size and scope to the Caltech data set (unfortunately, it cannot be released publicly for legal reasons). Table 1 provides an overview and further details on each data set's properties and statistics (see also Fig. 1).

We benchmark performance using the reasonable evaluation setting (50 pixel or taller under partial or no occlusion), standardizing aspect ratios as described in Section 3.4. For Daimler-DB and INRIA, which contain only grayscale and static images, respectively, we run only detectors that do not require color and motion information. Also, FTRMINE and FTRSYNTH results are not always available; otherwise, we evaluated every detector on every

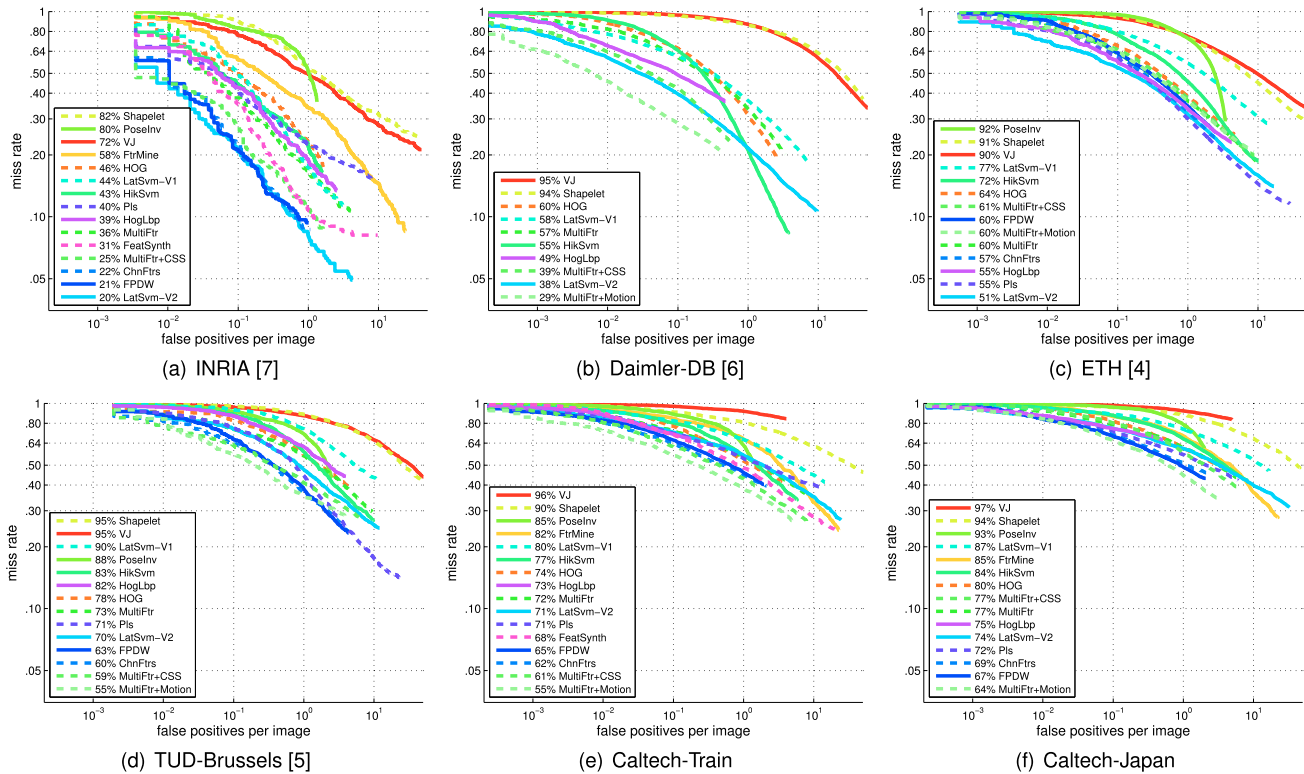


Fig. 13. Results on six data sets under the reasonable evaluation setting. In general, detector ranking is fairly stable across data sets. Best results are achieved on INRIA (a), which contains high-resolution pedestrians, followed by Daimler-DB (b), likely due to the good image quality. Overall performance for ETH (c), TUD-Brussels (d), Caltech-Train (e), and Caltech-Test (Fig. 11f) are similar. Performance on Caltech-Japan (f) is slightly worse, likely due to more challenging imaging conditions. The fairly high consistency of detector ranking across multiple data sets implies that evaluation is not overly dependent on the data set used.

data set. We make all data sets, along with annotations and detector outputs for each, available in a single standardized format on our project webpage.

Of all data sets, performance is best on INRIA, which contains high-resolution pedestrians, with LATSVM-V2, CHNFTRS, and FPDW achieving log-average miss rates of 20-22 percent (see Fig. 13a). Performance is also fairly high on Daimler-DB (Fig. 13b) with 29 percent log-average miss rate attained by MULTIFTR+MOTION, possibly due to the good image quality resulting from use of a monochrome camera. ETH (Fig. 11c), TUD-Brussels (Fig. 13d), Caltech-Training (Fig. 13e), and Caltech-Testing (Fig. 11f) are more challenging, with log-average miss rates between 51-55 percent, and Caltech-Japan (Fig. 13f) is even more difficult due to lower image quality. Overall, detector ranking is reasonably consistent across data sets, suggesting that evaluation is not overly dependent on the data set used.

### 5.3 Statistical Significance

We aim to rank detector performance utilizing multiple data sets and assess whether the differences between detectors are statistically significant. Two issues make such an analysis challenging: 1) Data set difficulty varies and 2) relative detector performance may change across data sets. The plots in Fig. 13 clearly demonstrate both challenges. To address this, Demšar [87] introduced a series of powerful statistical tests that operate on an  $m$  data set by  $n$  algorithm performance matrix (e.g., a matrix of log-average miss rates). The key insight is to convert absolute performance on each data set into algorithm *rank*, thus removing the effects

of varying data set difficulty. We first describe the analysis and then present results for pedestrian detectors.

We analyze statistical significance using the nonparametric Friedman test with a posthoc analysis; this approach was also used by Everingham et al. [14] for the PASCAL VOC challenge. Contrary to ANOVA, the Friedman test does not assume a distribution on performance, but rather uses algorithm ranking. Demšar [87] found this nonparametric approach to be more robust. A further in-depth study by García and Herrera [88] concluded that the Nemenyi posthoc test which was used by Demšar [87] (and also in the PASCAL challenge [14]) is too conservative for  $n \times n$  comparisons such as in a benchmark. They recommend use of more powerful posthoc tests such as the Shaffer test that include more sophisticated logic reasoning. For our analysis we use the nonparametric Friedman test along with the Shaffer posthoc test (code is available from [88]).

To obtain a sufficient number of performance samples we evaluate the pretrained detectors separately on each of the 11 sets in the Caltech data set (see Section 2.3), 13 sets of Caltech-Japan, three sequences in ETH, and one sequence in TUD-Brussels. We omit Daimler-DB and INRIA on which not all detectors can be tested and any detector not tested on every data set (see Section 5.2). We rank detectors on each data fold based on their log-average miss rate (tested under the reasonable evaluation setting). This procedure yields a total of 28 rankings for 14 detectors.

Results are shown in Fig. 14. First, we plot the number of times each detector achieved each rank in Fig. 14a. Detectors are ordered by improving mean rank (displayed



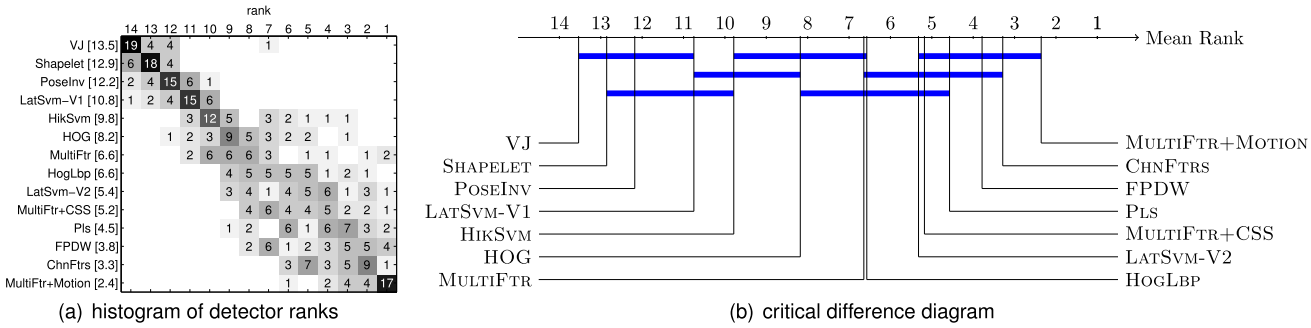


Fig. 14. Summary of detector performance across multiple data sets and the statistical significance of the results. (a) Visualization of the number of times each detector achieved each rank. Detectors are ordered by improving mean rank (displayed in brackets); observe the high variance among the top performing detectors. (b) Critical difference diagram [87]: The  $x$ -axis shows mean rank, blue bars link detectors for which there is insufficient evidence to declare them statistically significantly different (due to the relatively low number of performance samples and fairly high variance).

in brackets). The best overall performing detector is MULTIFTR+MOTION, which ranked first on 17 of the 28 data folds and had a mean rank of 2.4. CHNFTRS and FPDW came in second and third with a mean rank of 3.3 and 3.8, respectively. VJ has the worst overall performance with a mean rank of 13.5, while HOG remains somewhat competitive with a mean rank of 8.2. Among the top performing detectors, however, variance is fairly high, with nearly every detector from MULTIFTR onward ranking first on at least one data fold.

Fig. 14b shows the results of the significance test for a confidence level of  $\alpha = 0.05$ . The  $x$ -axis shows mean rank for each detector, blue bars link detectors for which there is insufficient evidence to declare them statistically significantly different. For example, MULTIFTR+MOTION, CHNFTRS, and FPDW are all significantly better than HOG (since they are not linked). Observe, however, that the differences between the top six detector are not statistically significant; indeed, each detector tends to be linked to numerous others. This result does not change much if we relax the confidence to  $\alpha = 0.1$ . A similar trend was observed in Everingham et al.’s [14] analysis on the PASCAL challenge. Unfortunately, the statistical analysis requires a large number of samples, and while the 28 data folds provide a considerably more thorough analysis of pedestrian detectors than previously attempted, given their inherent variability even more data would be necessary. We emphasize, however, that simply because we have insufficient evidence to declare the detectors statistically significantly different does *not* imply that their performance is equal.

### 5.4 Runtime Analysis

In many applications of pedestrian detection, including automotive safety, surveillance, robotics, and human machine interfaces, fast detection rates are of the essence. Although throughout we have focused on accuracy, we conclude by jointly considering both accuracy and speed.

We measure runtime of each detector using images from the Caltech data set (averaging runtime over multiple frames). To compensate for detectors running on different hardware, all runtimes are normalized to the rate of a single modern machine. We emphasize that we measure the speed of binaries provided by the authors and that faster implementations are likely possible.

In Fig. 15, we plot log-average miss rate versus runtime for each detector on  $640 \times 480$  images. Legends are ordered by detection speed measured in frames per second (fps). Detection speed for pedestrians over 100 pixels ranges from  $\sim 0.02$  to  $\sim 6.5$  fps achieved by FPDW, a sped up version of CHNFTRS. Detecting 50 pixel pedestrians typically requires image upsampling; the slowest detectors require around 5 *minutes* per frame. FPDW remains the fastest detector operating at  $\sim 2.7$  fps. Overall, there does not seem to be a strong correlation between runtime and accuracy. While the slowest detector happens to also be the most accurate (MUTLIFTR+MOTION), on pedestrians over 50 pixels the two fastest detectors, CHNFTRS and FPDW, are also the second and third most accurate, respectively.

While the frame rates may seem low, it is important to mention that all tested detectors can be employed as part of a full system (cf. [2]). Such systems may employ ground

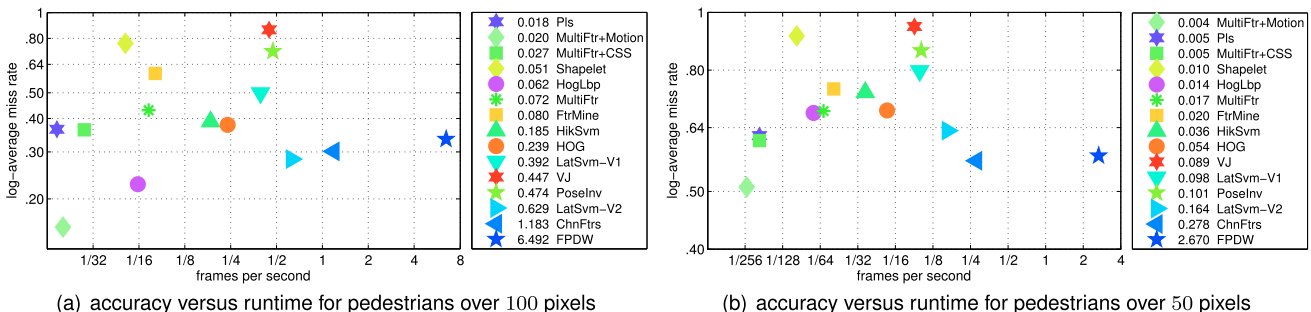


Fig. 15. Log-average miss rate versus the runtime of each detector on  $640 \times 480$  images from the Caltech Pedestrian Data Set. Runtimes of all detectors are normalized to the rate of a single modern machine; hence all times are directly comparable. (Note that the VJ implementation used did not utilize scale invariance; hence its slow speed.) While the slowest detector happens to also be the most accurate (MUTLIFTR+MOTION), for pedestrians over 50 pixels the two fastest detectors, CHNFTRS and FPDW, are also the second and third most accurate, respectively.

plane constraints and perform region-of-interest selection (e.g., from stereo disparity or motion), reducing runtime drastically. Moreover, numerous approaches have been proposed for speeding up detection, including speeding up the detector itself [29], [44], [46], through use of approximations [63], [89] or by using special purpose hardware such as GPUs [90] (for a review of fast detection see [63]). Nevertheless, the above runtime analysis gives a sense of the speed of current detectors.

## 6 DISCUSSION

This study was carried out to assess the state of the art in pedestrian detection. Automatically detecting pedestrians from moving vehicles could have considerable economic impact and the potential to substantially reduce pedestrian injuries and fatalities. We make three main contributions: a new data set, an improved evaluation methodology, and an analysis of the state of the art.

First, we put together an unprecedented object detection data set. The data set is large, representative, and relevant. It was collected with an imaging geometry and in multiple neighborhoods that match likely conditions for urban vehicle navigation. Second, we propose an evaluation methodology that allows us to carry out probing and informative comparisons between competing approaches to pedestrian detection in a realistic and unbiased manner. Third, we compare the performance of 16 pretrained state-of-the-art detectors across six data sets. Performance is assessed as a function of scale, degree of occlusion, localization accuracy, and computational cost; moreover, we gauge the statistical significance of the ranking of detectors across multiple data sets.

All results of this study, and the tools for reproducing them, are posted on the project website.<sup>3</sup> This includes the Caltech Pedestrian Data Set, the video annotation tool (see Fig. 3), and all evaluation code. We have also posted all additional data sets used in this study (INRIA, TUD-Brussels, ETH, and Daimler-DB), along with their annotations and detector outputs on each, in a standardized format. The goal is to allow all researchers to easily and accurately assess state-of-the-art performance.

Our experiments allow us to make a number of observations and point to important directions for further research. We discuss them in the following sections.

### 6.1 Statistics of the Caltech Pedestrian Data Set

The Caltech Pedestrian Data Set is thoroughly annotated (including occlusion labels, temporal correspondences, and “ignore” regions) and contains pedestrians at a wide range of scales. It thus allows us to analyze the statistics of a number of important phenomena:

**Scale.** Pedestrian pixel size is highly variable. Most pedestrians, however, are observed at heights of 30 to 80 pixels. This scale range also happens to be the most important for automotive settings given current sensor technology and typical imaging geometry (see Fig. 4).

**Occlusion.** Occlusion is very frequent (see Figs. 5b and 5c). Nevertheless, out of many possible occlusion patterns, few are commonly observed (see Fig. 5f). The head is

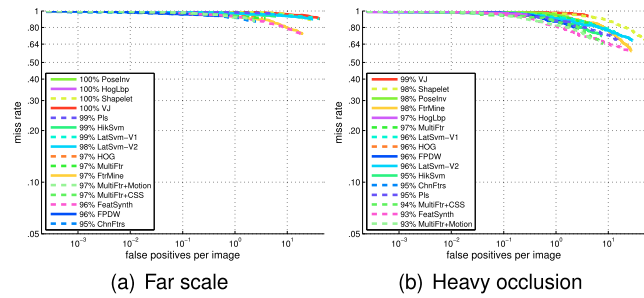


Fig. 16. Evaluation on far scales and for heavily occluded pedestrians. In both cases, detection performance is abysmal and currently outside the capabilities of the state of the art.

typically visible, while the lower portions of a pedestrian are increasingly likely to be occluded.

**Location.** The distribution of pedestrian centers in images is highly concentrated along the middle band (see Fig. 6a). However, while incorporating this constraint would speed detection, it would only moderately reduce false alarms under these settings (see Fig. 6b).

Experiments across multiple data sets show reasonably consistent detector rankings (see Figs. 13 and 14), suggesting that evaluation is not overly dependent on the data set used. Overall, however, the Caltech Pedestrians Data Set proves to be the most challenging. We thus expect that it will remain useful for a fairly long time before showing signs of saturation. Furthermore, its large size and thorough annotation enables researchers to measure performance under very low-false alarm rates, small scales, and varying levels of occlusion.

### 6.2 Overall Performance

There is considerable room for improvement in pedestrian detection. The plots in Fig. 11 show that:

1. Performance is far from perfect, even under the most favorable conditions. At the near scale, i.e., with pedestrians at least 80 pixels tall, 20-30 percent of all pedestrians are missed under the fairly mild goal of at most one false alarm every 10 images (see Fig. 11b).
2. Performance degrades catastrophically for smaller pedestrians (see Figs. 11c and 12). While pedestrians 30-80 pixels tall are most numerous and most relevant in automotive settings, around 80 percent are missed by the best detectors (at 1 false alarm per 10 images).
3. Performance degrades similarly under partial occlusion (under 35 percent occluded), see Fig. 11e.
4. Performance is abysmal at far scales (under 30 pixels) and under heavy occlusion (over 35 percent occluded), see Fig. 16. Under these conditions nearly all pedestrians are missed even at high false positive rates.

The gap between current and desired performance is large and unlikely to be reached without major leaps in our understanding. One should note that single frame performance is a lower bound for the performance of a full system and that tracking, contextual information, and the use of additional sensors can help reduce false alarms and improve detection rates (see [2]).

3. [www.vision.caltech.edu/Image\\_Datasets/CaltechPedestrians/](http://www.vision.caltech.edu/Image_Datasets/CaltechPedestrians/).

### 6.3 State-of-the-Art Detectors

While research in pedestrian detection is quite diverse, the approaches with the best performance have many elements in common (see Table 2). These detectors typically follow a sliding window paradigm which entails feature extraction, binary classification, and dense multiscale scanning of detection windows followed by nonmaximum suppression. Nearly all modern detectors employ some form of gradient histograms; in addition, the best performing detectors tend to use a combination of cues. Support vector machines and boosting are used almost exclusively although variants show promise. For multiscale detection, 10-14 scales per octave are commonly tested, and for NMS, mean shift mode estimation and pairwise max suppression appear most successful. Overall, there is a high degree of convergence for the various stages of detection.

Which is the best overall detector? Fig. 15 summarizes both detection accuracy and computational cost; surprisingly, there does not seem to be a hard tradeoff between these two quantities. Overall, FPDW has the most appealing characteristics: It is at least one order of magnitude faster than its competitors and has among the best detection rates, particularly on medium scale pedestrians. If computational cost is not a consideration, then MULTIFTR+MOTION is the best choice. Note, however, that retraining on the larger Caltech Pedestrian Data Set may change the relative ranking of the detectors.

The state of the art in pedestrian detection is clearly advancing. Considerable progress has been made from earlier approaches (e.g., VJ) to the most recent ones (see Table 2). Thus, given the fast pace of technical progress in the field and the considerable room for improvement, we expect to see new detectors top the charts every year.

### 6.4 Research Directions

Our benchmark indicates the need for research in seven areas:

1. Small scales. Better performance is needed in the 30-80 pixel range, while most research has been focused on pedestrians over 100 pixels. Reasonable human performance at medium scales indicates that detection in this range is achievable without resorting to expensive high-resolution cameras that would delay the introduction of machine vision systems to automotive settings.
2. Occlusion. Performance degrades rapidly under even mild occlusion, including for part-based detectors. The Caltech Pedestrian Data Set is the first to include occlusion labels (and a study of occlusion statistics); we hope this motivates researchers to improve this.
3. Motion features. The detector with highest accuracy (MULTIFTR+MOTION) is the only one to utilize motion features, but the optical flow-based features appear to help primarily at large scales. At low resolutions, motion is very informative for human perception; thus effective motion features for this setting are needed.
4. Temporal integration. Although full systems often utilize tracking (e.g., see [2], [6], [42]), a comparative study of approaches for integrating detector outputs

over time has not been carried out. Note that full tracking may be unnecessary and methods that integrate detector outputs over a few frames may suffice [41].

5. Context. The ground plane assumption can reduce errors somewhat; however, at low resolutions more sophisticated approaches for utilizing context are needed.
6. Novel features. The best detectors use multiple feature types in combination with gradient histograms (see Table 2). We expect additional gains from continued research on improving feature extraction.
7. Data. Most detectors were trained on INRIA [7]. Training using the much larger Caltech data set should boost performance, although learning becomes more challenging due to the broad range of scale and occlusion levels. Studies are needed to see the effect of quantity and type of training data versus performance.

### ACKNOWLEDGMENTS

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