Improved Handling of Motion Blur in Online Object Detection

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Abstract

We wish to detect specific categories of objects, for online vision systems that will run in the real world. Object detection is already very challenging. It is even harder when the images are blurred, from the camera being in a car or a hand-held phone. Most existing efforts either focused on sharp images, with easy to label ground truth, or they have treated motion blur as one of many generic corruptions.

Instead, we focus especially on the details of egomotion induced blur. We explore five classes of remedies, where each targets different potential causes for the performance gap between sharp and blurred images. For example, first deblurring an image changes its human interpretability, but at present, only partly improves object detection. The other four classes of remedies address multi-scale texture, out-of-distribution testing, label generation, and conditioning by blur-type. Surprisingly, we discover that custom label generation aimed at resolving spatial ambiguity, ahead of all others, markedly improves object detection. Also, in contrast to findings from classification, we see a noteworthy boost by conditioning our model on bespoke categories of motion blur. We validate and cross-breed the different remedies experimentally on blurred COCO images, producing an easy and practical favorite model with superior detection rates.

1. Introduction

A little motion blur is present in most hand-held photography. Blur is ever harder to ignore because images are increasingly captured on the move, e.g. by a gimbaled robot or from an autonomous vehicle. Precisely these on-the-go situations prompt us to explore: how much does motion blur severity impact object detection? What can be done about it? Detection is important because it underpins many other tasks, such as tracking and re-identification, and our initial scope is further narrowed to egomotion induced blur.

Unsurprisingly, the severity of the blur correlates with detection failure [2]. Fig. 1 shows an example. An ideal algorithm will make that degradation more gradual, and could someday enable a model that surpasses even a human’s ability to see through blur. Instead of a single breakthrough, it is more likely that a combination of approaches is needed. Much like the “devil in the details” papers [6, 7], the task specifics and pipeline likely make a difference.

Our main contribution is an empirical exploration of five classes of remedies. These remedies are selected to cope with five proposed causes for reduced detection accuracy. The five cause/remedy pairs explored here are:

1. Is the entire image too blurry to be useful?
   • Deblur test image first.

2. Is texture mismatch at different scales confusing the network?
   • Spatially transform image to compensate.

3. Does test-time blur differ from training data?
   • Train model for out-of-distribution robustness.
   • Perform test-time tuning of network.

4. Are the training labels incorrect?
   • Customize labels to match detection-in-blur task.
   • Reconsider labels used for testing.

Figure 1. a) Original sharp MS COCO [24] image with object detections. b) Same image with significant linear motion-blur, with COCO ground-truth. c) Failed predictions from original Faster-RCNN. d) Predictions from network with our proposed model.
Deblurring: A close topic with valuable data and potential insights is image deblurring. The first canonical method for image deconvolution comes from Richardson [35] and Lucy [26] where a known point spread function (PSF) - the blur kernel - is used to iteratively minimize an energy function.

2. Related Work

Deblurring: A close topic with valuable data and potential insights is image deblurring. The first canonical method for image deconvolution comes from Richardson [35] and Lucy [26] where a known point spread function (PSF) - the blur kernel - is used to iteratively minimize an energy function.

5. Are egomotion blur types too diverse?

- Treat detection in blur as a multi-task problem.
function to find a maximum likelihood estimate of the original image. Deblurring can be non-blind where the blur kernel is known [38], or it can be blind, where the kernel is either first estimated [11, 40] - usually optimized with the final result [8] - or the entire deblurring method is non-interpretable and runs end to end [28, 44]. Deblurring can also assume either a uniform blur kernel throughout an image [11, 40] or variable nonuniform blur either due to camera egomotion (rotation, zoom) [46] or dynamic object motion blur [18, 28].

Previous work has made use of an L0 sparse representation [47], dark image regions [29], and multiple frames in a video [41]. Many invasive methods exploit hardware, including using a coded shutter [32], inertial measurements [21], flash frame information integration [51], bursts of blurry images [1], high and low frame rate cameras [43], or an event driven camera tied to an RGB sensor [30].

Some deep learning deblurring methods are interpretable [40, 5, 48, 42], but most are end-to-end [44, 22, 49, 28] with the recent state-of-the-art by Nah et al. trained on the high frame rate GOPRO dataset [28]. We explore using a state-of-the-art deblurring method as a preprocessing step, and measure the overall effectiveness of such a baseline.

Boracchi et al. [3] generate a statistical model for motion blur kernel generation and benchmark image restoration model performance with variable motion blur parameters. The motion trajectories and subsequent blur kernels they generate are parameterized based on camera shake and exposure. This makes their kernel generation method a good candidate for synthesized blur augmented training.

Although deblurring’s aesthetics driven approach means that there are competitive methods for extracting high frequency information in the worst blur scenarios, use in an online vision application might be impractical, especially given that networks are very sensitive to changes in training distribution. **Blur and Scene Understanding Tasks:** Directly related to this work, Vasiljevic et al. [45] explore the effect of blur on ImageNet [10] classification performance using a set of synthetically generated blur kernels. Although they explore augmentation strategies and the effect of motion blur on classification accuracy, they use a limited set of 100 17 × 17 pre-generated fixed length motion blur kernels and a restrictive image resolution of 384 × 384 during training and evaluation. While they explore the effect of different blur types on images for classification, they only explore defocus blur for image segmentation. Fine grained blur augmentation is explored for classification, however only a segmentation dividing blur types and not across blur exposure with different kernel types is considered. While the authors mention the possibility of having blur information in the image apriori, they do not explore a blur estimation component, nor do they explore a complete end to end framework for running specialized networks. For image segmentation, they evaluate their networks using a soft boundary for accuracy, but do not explore the effect of spatial ambiguity on fine-tuning networks for blur during training, especially given only defocus blur (no shift in barycenter naturally) is used for fine-tuning the segmentation task.

Overall, we find that building explicit robustness into vision models for dealing with realistic camera motion blur needs more exploration.

**Out-of-Distribution Robustness:** Recent work [15, 14] treats image corruptions (brightness, contrast, snow, noise, blur) as out-of-distribution samples compared to the in-distribution clean images a network was trained on. ImageNet-C [15] is a variant of the ImageNet classification dataset that contains images corrupted by 15 different types of canonical image corruptions. It’s aimed at being an out-of-distribution representation of image corruptions that models can be benchmarked on. Crucially, ImageNet-C - and others such as ImageNet-R [14] and ImageNet-A [17] - are not meant to be trained on. Instead, the argument is that a model’s ability to generalize to images outside of the training set’s distribution can be measured by evaluating its performance on these datasets. Although ImageNet-C contains motion blur corruptions, the method only considers straight line motion blur kernels. Michaelis et al. [27] use the same corruptions from ImageNet-C to produce a robustness benchmark for detection, by augmenting MS COCO [24]. COCO-C also includes straight line blurred images, but changes in labels under the spatial ambiguity brought upon by blur are not addressed. We call this type of non-centered blur ‘Naive,’ and we show why it’s important for spatial reasoning.

AutoAugment [9] is an outer loop augmentation framework that finds an optimal augmentation policy for a model and dataset pair. Although the method achieves state-of-the-art accuracy for multiple classification datasets, it requires 15,000 compute hours on an NVIDIA Tesla P100 for training ImageNet. Rusak et al. [37] propose an adversarial noise training scheme for increasing classification model accuracy and robustness on ImageNet-C; the is aimed at combating pixel noise and not blur. AugMix [16] is an augmentation strategy for improving classification model robustness to out-of-distribution images. It involves alpha blending copies of a training image that have been corrupted by a random chain of image augmentations. They use the same corruptions in AutoAugment, including both pixel level value changes and spatial augmentations. Although the AugMix paper also doesn’t discuss how spatial augmentation should affect spatial labels, we explore the effectiveness of AugMix for blur robustness after making decisions on how spatial labels should be changed.

Schneider et al. [39] analyze the effect of normalizing activations in batch normalization layers using a weighted
average of the statistics of both the source training set and the minibatch. Their method achieves state-of-the-art on ImageNet-C and improves ImageNet-C robustness on vanilla Resnet-50 classification models, even with a minibatch of size one.

While these methods are a promising way of increasing model robustness to unseen corruptions, the aim of the proposed work is to explore the specific impact of motion blur on detection, and so we focus our effort on manufacturing the most realistic blur kernels available in the literature.

3. Designing Detection Models for Motion Blur

To improve online object detection, we propose a unified framework that allows us to measure the impact of different remedies and their combinations. The framework is based on a state-of-the-art object detector, Faster-RCNN [34], with training and testing on data derived from the MS COCO [24] detection dataset. The baseline and data are explained in this section. The proposed remedies are explained in detail in Sec. 4, and are evaluated in Sec. 5. Figure 2 illustrates both the baseline model, and the different enhanced alternatives.

3.1. Detection Baseline

For reproducibility, we use the pretrained Faster R-CNN variant trained on COCO, available through Pytorch’s [31] torchvision library, as a baseline for all our experiments. We use a ResNet-50 [13] backbone with a Feature Pyramid Network (FPN) [23]. This baseline achieves 58.5 mAP@0.5 and 37.0 mAP@0.5:0.95 on the COCO test set. While other models achieve better accuracy on the COCO minival set, we choose this framework for its accessibility and as a good baseline representation of a canonical detection framework with top-10 performance for the backbone’s size [20, 25].

3.2. Selecting Data for Training and Testing

Ideally, we’d select data with detection labels for images exhibiting motion blur. Due to the way MS COCO is gathered [24], there are very few blurry images in the dataset. This leaves us with the task of generating synthetically blurred COCO images for both training and evaluation. Related but not directly applicable here, there are multiple real-world image datasets for deblurring. These were generated using high frame rate video [28] or shutter tied cameras [36]. They either don’t contain enough images for training and evaluating detection models ([36] only contains 5500 images) and/or lack object annotations. Zhang et al. [50] generate blurry images as part of a GAN architecture for deblurring. Although they train the blur generation module using a discriminator trained on real world blurry images, it is not trivial to modify labels, given spatial ambiguity, since camera motion is not made explicit. Brooks & Barron [4] use multiple adjacent images (as few as two) to generate realistic motion blur. But to use that would require a video or stereo dataset with ground truth labels for the detection task.

This leaves methods that synthesize blurry images via convolution with synthetic motion blur kernels [38, 3, 45, 27, 15]. ImageNet-C [15] and COCO-C [27] contain images blurred using straight line motion blur exclusively, with no control over simulated camera shake. Vasiljevic et al. [45] use a limited set of motion-blur kernels since they are constrained by a fixed length spline formation model. Boracchi & Foi [3] describe a method that allows control over different characteristics of a camera’s trajectory through space, including the amount of shake and jerk with variable exposure.

3.3. Blur Generation and Space Discretization

We adapt the blur kernel generation method from Boracchi & Foi [3]. We fix their high level controllable parameter $P$ to one of three values, $P_{1-3}$, representing three distinct types of camera motion. We also modulate exposure via early camera trajectory clipping.

First, we generate a trajectory by finding a random path in 2D space. We assign an initial velocity vector $v_0$, drawn at random from a unit circle, and a position in space $x_0$ for the camera. At every step, the camera’s velocity vector is updated by the acceleration vector, $\Delta v = P(\Delta v_g - I x_t)$, (1)

where $\Delta v_g$ is random acceleration with elements drawn
from $\mathcal{N}(0, \sigma^2)$. $I_{x_4}$ is an inertial tendency for the camera to stay where it is, and $P \in P_{1-3}$ is the high level anxiety parameter we fixed above. $P_3$ has the highest random velocity change on every step. Further, to model a camera jerk, with a randomly sampled indicator function, the acceleration update also includes a component equal to twice the current velocity vector in a random direction, so

$$\Delta v = \Delta v + 2P|V|\Delta v_j,$$ (2)

where $\Delta v_j$ is sampled from the unit circle. Again, with a high $P$, there is a higher chance of a jerk happening and a shakier camera. When starting a trajectory, with high $P$, there is a higher chance of a jerk happening and a shakier camera. When starting a trajectory, $I$, $\sigma^2$, and $\theta$ are drawn once from uniform random distributions to increase variability under the same class of blur $P \in P_{1-3}$. Note that this leads to some overlap between kernels generated across different $P$s.

In summary, the type of camera behavior falls into one of three classes: 1) $P_1$ simulates a very nervous camera, 2) $P_2$ for back and forth behavior, and 3) $P_3$ simulates mostly straight rectilinear motion-blur. To simulate exposure, we stop the motion path early using the exposure factor (trajectory length) $E$. We discretize exposure to one of $5$ values, $E_{1-5}$. Examples of these kernels can be seen in Fig. 3. Sub-pixel interpolation produces kernels for convolving sharp images.

### 3.4. Implementation Details

**Kernel Generation:** To speed up training, a corpus of 12,000 blur kernels is generated for every pair of $\{P_{1-3}\} \times \{E_{1-5}\}$, for a total of 180,000 possible motion blur kernels. However, random kernels are generated on the fly during evulation for each combination of blur type and exposure, with fixed seeds for reproducibility. Trajectory length is 96 and blur kernels fit in $128 \times 128$ filters.

**Blurring:** Unlike in [15, 45, 27], we don’t resize images to a fixed size before blurring. Instead each image is convolved separately with reflection padding, to account for what would otherwise be real world data. We opt not to resize our blur kernels to match image size as a way of simulating changes in focal length. We implement sparse convolution on the GPU for applying blur kernels. As per Sec. 4.4, we make sure to center our motion-blur kernels by translating their barycenters to the center of the filters.

**Training:** All networks start from a base ResNet-50FPN pretrained on COCO. We use an FPN framework that outputs activations at four scales from the backbone. There was no apparent difference in blur augmented performance when training all five blocks vs. fixing the weights of the first two.

### 4. Proposed Remedies for Improved Detection

Suspecting specific underlying causes for the adverse effects of blur on detection, we now propose bespoke remedies. Where appropriate, some of the remedies are also crossbred, and experimental results appear in Sec. 5.

#### 4.1. Deblurring as a Pre-process

Image deblurring is useful for aesthetic purposes, but could also aid other vision tasks. To test this remedy, we use the recent deblurring model from the GoPro dataset paper, [28], before passing the result to the detector. Deblurring is a slow process, by $12 \times$ in this case, so heavy optimizations would be needed for an online robot.

#### 4.2. Reconciling Texture Information With Scale

When motion-blur is biased to one major direction over another, it removes more high frequency information (and texture) in that direction. It is reasonable to expect a network is not natively designed for this imbalance. CNNs usually understand texture and shape information across multiple scales under the same aspect ratio, but we’re also asking the network to deal with a texture imbalance along the blur kernel’s major axis. Influenced by the work on Spatial Transformers [19] (which proved a slightly inferior baseline) and neural sampling layers [33], we instead undersample the incoming image along the direction where the blur kernel is most severe. For best-case testing, an oracle is assumed to know the blur kernel. We then find the principal component strength values, $\lambda_1$ and $\lambda_2$, and a direction, $\theta$, on which these principal components lie. We apply an affine transform to the image by first rotating using $\theta$, striding using scaled versions of $\lambda_1$ and $\lambda_2$, and then rotating back before passing the transformed image to the backbone. The reverse operation is carried out, using reciprocal scaling factors, on every activation output from the backbone. This “Squint” process is done at both train and test time.

#### 4.3. Training vs. Test Distribution

Recent work treats corrupted images as being out-of-distribution (OOD) compared to sharp images in the dataset [15, 27, 16, 39]. We consider treating complex motion-blur as an out-of-distribution corruption, and use two promising methods from the OOD literature. We use AugMix [16] as a training time remedy. We propose three flavors, the first is a purely pixel level version where we augment pixel intensities only. The second applies all spatial augmentations as well, but does not reconcile the shifts in bounding box changes. The third is an “Expanded” version following Sec. 4.4, where we change COCO labels at train time to match the superset of where an object is shifted to across branches. AugMix roughly approximates blur when augmentations are selected that translate an image before concatenating with other branches.

Further, at test time, we use covariate shift adaptation from the upcoming [39]. The first step is to get a weighted
average of the incoming activation statistics of the mini-batch ($n = 1$ for online inference) and the source statistics of the model where $N = 16$,

$$
\mu = \frac{n \mu_t + N}{N + n} \mu_s, \quad \sigma^2 = \frac{n \sigma^2_t + N}{N + n} \sigma^2_s.
$$

We then use these new normalization statistics for batch normalization in all network layers.

### 4.4. Customizing Labels

When an image is motion blurred, objects are no longer confined to the bounding boxes they had occupied in the sharp image. The objective may no longer be to estimate that original bounding box. See Fig. 4. We discuss two remedies for this problem, that apply when training under augmentation and for evaluation.

**Kernel Centering** The start point of a motion blur path corresponds to the exposure at $t = 0$. Any path that leads away from the center, as in Fig. 4(b), will offset the blurred version of the object in some direction. After that convolution, the “ground truth” bounding box is no longer centered on the blurred object. This introduces a mismatch between the blurred input and the label. This mismatch is created in ImageNet-C [15] and COCO-C [27], introducing ambiguity and noise in training.

We center a kernel using a weighted average of the kernel’s nonzero points. The aim is to have the detection framework learn to localize objects based on where they are, on average, during the exposure. It turns out this remedy is similar to how [36] aligned images from paired long/short exposure cameras to train for deblurring. In our case, the training loss is noisier when training on non-centered kernels, and the drop in accuracy can be up to 8-10mAP@50 (see Fig. 5) points with the most severe blur. All networks shown here will be trained and evaluated with centered kernels, except when explicitly mentioned. We include ablation experiments with no-centering in the supplemental.

**Expanding Target Boxes** Compared to the original bounding box, the expanded label can cover the superset of pixels where an object projected during an exposure; see Fig. 4(d). A worst-case scenario could occur without this correction during training: for a small object, the sharp image’s label could seemingly miss the blurred object entirely due to IOU cutoffs. As a remedy, for every generated centered kernel, we find the maximum offsets for non zero kernel elements in both 2D axes, $x^-, x^+, y^-, y^+$, and use them to expand the boundaries of COCO bounding box labels. The new bounding box labels (top left and width/height) are now

![Figure 4](image-url)

Figure 4. a) An image from the MS COCO [24] trainset with an associated bounding box label. b) The same image but blurred and with the same non-translated bounding box, now introducing a training/evaluation mismatch. The object may have been there at the start of the exposure (or end if the kernel smeared the other way), but this is certainly not true for the rest of the image. c) The first remedy, centering the kernel by shifting the barycenter of the nonzero points to the center of the filter. d) The object is smeared outside of the original COCO bounding box, so the label is expanded using the filter’s max/min points to capture the superset of object locations.

![Figure 5](image-url)

Figure 5. Comparison of detection accuracy (averaged across all blur types) with the kernel-centering correction during training (blue) and without (red).
\[ \hat{b}_x = b_x - |x^-| \\
\hat{b}_y = b_y - |y^-| \\
\hat{b}_w = b_w + |x^-| + |x^+| \\
\hat{b}_h = b_h + |y^-| + |y^+|. \] (4)

We train variants of our networks with these expanded boxes alongside kernel centering. During test time, we evaluate these networks using expanded bounding boxes.

### 4.5. Specializing for Categories of Blur

The final category of remedies explores if egomotion induced blur is perhaps multiple problems masquerading as one. We explore training blur specialized networks on specific partitioned segments of the blur space, as if categories of blur are multiple distinct tasks. The findings on recognition in [45] show that specialized networks can sometimes achieve higher task accuracy on their respective blur types than general blur augmented networks.

**Two Specialized Meta-Models** We make two sets of specialized networks, that differ in how the motion kernels are clustered into categories. First, motion blur is grouped based on the type of kernel \( P \), alone, leading to a bespoke network for each of \( P_{1-3} \).

The second grouping creates three networks specialized at each \( P \) but only on long exposure blur. One further network handles all low exposure blur. As per [12], networks are biased toward texture. Instead of using this knowledge to create more corruption robust networks, it is exploited here to make more shape biased networks for substantial motion blur.

**Blur Estimation and Network Selection** A ResNet-18 blur estimator module is added, and runs 10 \( \times \) faster than the detection framework. The estimator categorizes the blur present in the image at test time. One network is trained on 16 classes (sharp and the combinations of all exposures and blur types) and the other network focuses on the separation between specific blur types at high exposures and general blur at low exposure (four classes). Our blur estimator achieves an accuracy of 97\% across four classes.

### 5. Comparisons and Evaluation

We report COCO minival results for all proposed remedies, at both test time and train time. Detection accuracy at mAP@50 is reported for all below-listed models and variants in Fig. 6 and Fig. 7, where the former uses COCO original labels, and the latter uses expanded labels. Names in the figures are explained below, and map to the five remedy categories. Qualitative results here: https://www.youtube.com/watch?v=nNEN-hc2zeho.

- **Standard Augmented** and **Expanded Labels** were trained on non-expanded but centered COCO labels, and expanded and centered COCO labels respectively. Both were trained on a 10/90 mixture of sharp to blurry images across all blur types.

- **Deblur then original** and **Deblur then Standard Augmented** are both modes of operation where the image is first deblurred using [28] before going through either the original network or a **Standard Augmented** network respectively.

- **Squint and Squint Expanded Labels** are come from Sec. 4.2, and have been trained either using standard labels under blur or expanded labels, respectively.

- **AugMix** Hendrycks et al. [16] do not discuss how spatial labels should be adapted when applying spatial augmentations during training, so results are reported for a non spatial version, **AugMix PixelLevel**, a spatial version trained and evaluated on labels that have not been expanded **AugMix**, and a version that has seen labels expanded at training time due to spatial augmentations and is then evaluated on expanded labels under blur **AugMix Expanded Labels**.

- **Standard Augmented w/MiniBatch and Expanded Labels w/MiniBatch** follow Schneider et al. [39] and use modified minibatch normalization with \( N = 16 \) and \( n = 1 \) (as suggested in [39]) with networks that have been augmented for blur using either standard labels or expanded labels respectively.

- **Expanded Labels w/ NonSpatial AugMix** has been trained by first transforming the image using non spatial AugMix then blurring the image and training with expanded labels.

- **Spec by Type** is a bag of specialists each trained on all exposures of a particular type of blur; the right network for the image is selected using a blur estimator. Each network is trained with 10\% sharp and 90\% of random \( E_{1-5} \) blurred images for their respective type. The **Standard Augment** network is used when no blur is detected. **Spec by Exposure** is also a bag of specialists, but networks specialize across exposure as well. Each of three networks specializes in one \( P \), but only at long exposures, and one network handles all short exposures and sharp images. Those high exposure networks are trained exclusively on blurry images. Again a blur estimator trained for these classes selects the right network. **Spec by Type Expanded Labels** and **Spec by Exposure Expanded Labels** are obviously variants trained on expanded labels. These networks and associated mode of operation outperform the rest due to their exploiting of the texture vs bias trade-off and the use of an accurate blur estimator. Notably, the network responsible for sharp and low exposure blur recovers the accuracy lost on sharp images usually associated with blur augmentation networks.
Almost all methods and hybrids improve beyond the Original network. There is no benefit in augmenting for blur, and then using either minibatch statistics or a deblurer network.

The Spec by Exposure network ("Ours") excels at both ends of the exposure extremes, likely due to the biased training and specialization networks it enjoys. All expanded-box trained networks (with the exception of AugMix trained on expanded labels via spatial augmentation) perform better than their standard counterparts. Note that the network augmented with both non-spatial AugMix and blur augmentation (Brown) maintains accuracy for sharp images too, where other blur augmented networks slump.

6. Discussion

We achieve state-of-the-art object detection results for egomotion-blurred images. We have succeeded in identifying that two factors adversely affect detection in such images. The first is that labels for sharp images should be customized for the motion-blur domain. In our remedies, that means translating and expanding the bounding box labels to match the blurred versions of relevant objects. The second is that categories of motion blur are distinct enough for the model to be trained for each blur-category separately. Interestingly, the second factor is the opposite of what [45] found with recognition tasks, where mixing blur-types during training was effective.

Through our “differential diagnosis” approach, the other three factors explored here seem unpromising for explaining the destructiveness of blur on CNN-based detection. These negative results are not conclusive, as the remedies may simply be immature. For example, better deblurring may eventually restore missing texture at all scales.

In the future, to reduce the memory footprint of our favored solution, the blur-selector and distinct exposure-specific models could be combined into one multi-task model. They are already end-to-end differentiable, but then they could share layers. Further progress in this direction could benefit from a distilled dataset that allows for detection labels and blur from real data, perhaps through the use of event driven cameras or multi-camera datasets.

One clear limitation is that even sharp images have $< 60 \text{ mAP} @ 0.5$ detection accuracy with a realtime-capable backbone, before blur hurts the situation further. Depth or disparity data would help address scenes with dynamic blur, since the blur kernels are depth-dependent. 360-cameras, augmented as proposed here for COCO, could be beneficial for dealing with sharp or blurred target objects that are partially outside a typical camera’s field of view. The impact of our approach could be especially helpful in particular applications, such as drone-based following, where even brief interruptions in tracking can ruin a film.
References

[1] Miika Aittala and Frédou Durand. Burst image deblurring using permutation invariant convolutional neural networks. In Proceedings of the European Conference on Computer Vision (ECCV), pages 731–747, 2018. 3

[2] Gedas Bertasius, Lorenzo Torresani, and Jianbo Shi. Object detection in video with spatiotemporal sampling networks. In Proceedings of the European Conference on Computer Vision (ECCV), September 2018. 1

[3] Giacomo Boracchi and Alessandro Foi. Modeling the performance of image restoration from motion blur. IEEE Transactions on Image Processing, 21(8):3502–3517, 2012. 3, 4

[4] Tim Brooks and Jonathan T Barron. Learning to synthesize motion blur. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6840–6848, 2019. 4

[5] Ayan Chakrabarti. A neural approach to blind motion deblurring. In European conference on computer vision, pages 221–235. Springer, 2016. 3

[6] K. Chatfield, V. Lempitsky, A. Vedaldi, and A. Zisserman. The devil is in the details: an evaluation of recent feature encoding methods. In British Machine Vision Conference, 2011. 1

[7] K. Chatfield, K. Simonyan, A. Vedaldi, and A. Zisserman. Return of the devil in the details: Delving deep into convolutional nets. In British Machine Vision Conference, 2014. 1

[8] Liang Chen, Faming Fang, Tingting Wang, and Guixu Zhang. Blind image deblurring with local maximum gradient prior. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1742–1750, 2019. 3

[9] Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation strategies from data. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 113–123, 2019. 3

[10] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A Large-Scale Hierarchical Image Database. In CVPR09, 2009. 3

[11] Rob Fergus, Barun Singh, Aaron Hertzmann, Sam T Roweis, and William T Freeman. Removing camera shake from a single photograph. In ACM SIGGRAPH 2006 Papers, pages 787–794. 2006. 3

[12] Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness. arXiv preprint arXiv:1811.12231, 2018. 7

[13] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016. 4

[14] Dan Hendrycks, Steven Basart, Norman Mu, Saurav Kadamath, Frank Wang, Evan Dorundo, Rahul Desai, Tyler Zhu, Samyak Parajuli, Mike Guo, et al. The many faces of robustness: A critical analysis of out-of-distribution generalization. arXiv preprint arXiv:2006.16241, 2020. 3

[15] Dan Hendrycks and Thomas Dietterich. Benchmarking neural network robustness to common corruptions and perturbations. arXiv preprint arXiv:1903.12261, 2019. 3, 4, 5, 6

[16] Dan Hendrycks, Norman Mu, Ekin D Cubuk, Barret Zoph, Justin Gilmer, and Balaji Lakshminarayanan. Augmix: A simple data processing method to improve robustness and uncertainty. arXiv preprint arXiv:1912.02781, 2019. 2, 3, 5, 7

[17] Dan Hendrycks, Kevin Zhao, Steven Basart, Jacob Steinhardt, and Dawn Song. Natural adversarial examples. arXiv preprint arXiv:1907.07174, 2019. 3

[18] Tae Hyun Kim, Byeongjoo Ahn, and Kyoung Mu Lee. Dynamic scene deblurring. In Proceedings of the IEEE International Conference on Computer Vision, pages 3160–3167, 2013. 3

[19] Max Jaderberg, Karen Simonyan, Andrew Zisserman, et al. Spatial transformer networks. In Advances in neural information processing systems, pages 2017–2025, 2015. 2, 5

[20] Licheng Jiao, Fan Zhang, Fang Liu, Shuyuan Yang, Lingling Li, Zhixi Feng, and Rong Qu. A survey of deep learning-based object detection. IEEE Access, 7:128837–128868, 2019. 4

[21] Neel Joshi, Sing Bing Kang, C Lawrence Zitnick, and Richard Szeliski. Image deblurring using inertial measurement sensors. ACM Transactions on Graphics (TOG), 29(4):1–9, 2010. 3

[22] Orest Kupyn, Volodymyr Budzan, Mykola Mykhailych, Dmytro Mishkin, and Jiří Matas. Deblurgan: Blind motion deblurring using conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8183–8192, 2018. 3

[23] Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. Feature pyramid networks for object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2117–2125, 2017. 4

[24] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014. 1, 3, 4, 6

[25] Li Liu, Wanli Ouyang, Xiaoang Wang, Paul Fieguth, Jie Chen, Xinwang Liu, and Matti Pietikäinen. Deep learning for generic object detection: A survey. International journal of computer vision, 128(2):261–318, 2020. 4

[26] Leon B Lucy. An iterative technique for the rectification of astronomic image. The astronomical journal, 79:745, 1974. 2

[27] Claudio Michaelis, Benjamin Mitkovs, Robert Geirhos, Evgenia Rusak, Oliver Bringmann, Alexander S Ecker, Matthias Bethge, and Wieland Brendel. Benchmarking robustness in object detection: Autonomous driving when winter is coming. arXiv preprint arXiv:1907.07484, 2019. 3, 4, 5, 6

[28] Seungjun Nah, Tae Hyun Kim, and Kyoung Mu Lee. Deep multi-scale convolutional neural network for dynamic scene deblurring. In Proceedings of the IEEE Conference on Com-
Ramesh Raskar, Amit Agrawal, and Jack Tumblin. Coded shutter. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1628–1636, 2016. 3

Liyuan Pan, Cedric Scheerlinck, Xin Yu, Richard Hartley, Miaomiao Liu, and Yuchao Dai. Bringing a blurry frame alive at high frame-rate with an event camera. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6820–6829, 2019. 3

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alch´e-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019. 4

Ramesh Raskar, Amit Agrawal, and Jack Tumblin. Coded exposure photography: motion deblurring using fluttered shutter. In *ACM SIGGRAPH 2006 Papers*, pages 795–804. 2006. 3

Adria Recasens, Petr Kellnhofer, Simon Stent, Wojciech Matusik, and Antonio Torralba. Learning to zoom: a saliency-based sampling layer for neural networks. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 51–66, 2018. 2, 5

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pages 91–99, 2015. 4

William Hadley Richardson. Bayesian-based iterative method of image restoration. *JoSA*, 62(1):55–59, 1972. 2

Jaesung Rim et al. *Real-World Blur Dataset for Learning and Benchmarking Deblurring Algorithms*. PhD thesis, DIIST, 2020. 4, 6

Evgenia Rusak, Lukas Schott, Roland Zimmermann, Julian Bitterwolf, Oliver Bringham, Matthias Bethge, and Wieland Brendel. Increasing the robustness of dnn against image corruptions by playing the game of noise. *arXiv preprint arXiv:2001.06057*, 2020. 3

Uwe Schmidt, Carsten Rother, Sebastian Nowozin, Jeremy Jancsary, and Stefan Roth. Discriminative non-blind deblurring. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 604–611, 2013. 3, 4

Steffen Schneider, Evgenia Rusak, Luisa Eck, Oliver Bringmann, Wieland Brendel, and Matthias Bethge. Improving robustness against common corruptions by covariate shift adaptation. *Advances in Neural Information Processing Systems*, 33, 2020. 2, 3, 5, 7

Christian J Schuler, Michael Hirsch, Stefan Harmeling, and Bernhard Schölkopf. Learning to deblur. *IEEE transactions on pattern analysis and machine intelligence*, 38(7):1439–1451, 2015. 3

[9] Shuo Chen Su, Mauricio Delbracio, Yue Wang, Guillermo Sapiro, Wolfgang Heidrich, and Oliver Wang. Deep video deblurring for hand-held cameras. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1279–1288, 2017. 3

[42] Jian Sun, Wenfei Cao, Zongben Xu, and Jean Ponce. Learning a convolutional neural network for non-uniform motion blur removal. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 769–777, 2015. 3

[43] Yu-Wing Tai, Hao Du, Michael S Brown, and Stephen Lin. Image/video deblurring using a hybrid camera. In *2008 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8. IEEE, 2008. 3

[44] Xin Tao, Hongyun Gao, Xiaoyong Shen, Jue Wang, and Ji-aya Jia. Scale-recurrent network for deep image deblurring. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 8174–8182, 2018. 3

[45] Igor Vasiljevic, Ayan Chakrabarti, and Gregory Shakhnarovich. Examining the impact of blur on recognition by convolutional networks. *arXiv preprint arXiv:1611.05760*, 2016. 3, 4, 5, 7, 8

[46] Oliver Whyte, Josef Sivic, Andrew Zisserman, and Jean Ponce. Non-uniform deblurring for shaken images. *International journal of computer vision*, 98(2):168–186, 2012. 3

[47] Li Xu, Shicheng Zheng, and Jiaya Jia. Unnatural l0 sparse representation for natural image deblurring. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1107–1114, 2013. 3

[48] Xiangyu Xu, Jinshan Pan, Yu-Jin Zhang, and Ming-Hsuan Yang. Motion blur kernel estimation via deep learning. *IEEE Transactions on Image Processing*, 27(1):194–205, 2017. 3

[49] J. Zhang, J. Pan, J. Ren, Y. Song, L. Bao, R. W. H. Lau, and M. Yang. Dynamic scene deblurring using spatially variant recurrent neural networks. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2521–2529, 2018. 3

[50] Kaimao Zhang, Wenhan Luo, Yiran Zhong, Lin Ma, Bjorn Stenger, Wei Liu, and Hongdong Li. Deblurring by realistic blurring. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2737–2746, 2020. 4

[51] Shaojie Zhuo, Dong Guo, and Terence Sim. Robust flash deblurring. In *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 2440–2447. IEEE, 2010. 3
1. Blur Discretization and Blur Space Segmentation

1.1. Discretization

In the main paper, $P$ and $E$ are held to discrete values. $P_{1-3}$ are [0.005, 0.001, 0.00005], where a lower value for $P$, $P_3$ for example, gives a more rectilinear blur. Since there are underlying random factors initialized for every blur kernel that are only influenced by $P$, some overlap exists between the type of blur kernels produced across different $P$s. Exposures $E_{1-5}$ are $[1/25, 1/10, 1/5, 1/2, 1]$.

All mAP@50 scores are reported on the COCO minival set (5000 images). We use a fixed seed for every evaluation when generating blur kernels.

While our proposed model was trained with those discrete blur settings, the space of camera-induced blur is not so neatly quantized. To explore a larger cross-section of the continuous blur space, we evaluated a sweep across a random selection of exposures (horizontal axis) and blur types (vertical axis), comparing the original network against our **Specialized by Exposure Expanded Labels**. Each marker plotted in Fig. 1 is an evaluation on 2000 images from the COCO minival set. It visually summarizes that for sharp and barely-blurred images, our approach is negligibly better than the original model. But for essentially all other settings of induced motion blur, our model does measurably better.

![Figure 1](image-url)

Figure 1. Comparison of the original model (ResNet50FPN trained on COCO) and our best model evaluated on expanded labels across a random selection of $P$ and $E$ values. Each marker is a representation of the accuracy (mAP@50) on an evaluation of 2000 images from the COCO minival. For the first two graphs (left to right), the greener the marker the closer it is to an mAP@50 of 61%. The redder it is, the closer it is to an mAP@50 of 0%. For the third graph, we visualize the difference between both networks; the greener the marker the larger the difference in mAP@50 between our best solution and the original network. The bluer the marker the less the difference is in accuracy. Naturally, at lower exposures, the original network holds up well, but as the exposure is ramped up, and particularly with more rectilinear blur (low $P$ value), the difference is much larger.

1.2. Segmenting Blur Space: By Type vs. By Exposure

All general augmented networks (non-specialized) are trained with a mixture of sharp COCO images (10%) and a random selection of blurry images across $P_{1-3}$ and $E_{1-5}$ (90%). **Spec by Type** networks are also trained on the same ratio, but are fixed to a specific $P$. The low exposure network in **Spec by Exposure** is trained on 25% sharp images and 75% blurry images from $P_{1-3}$ and $E_{1-3}$; the three others are trained on 100% blurry images exclusively from a specific $P$ and $E_{4,5}$. 
2. Zero Centering Ablation

We show how kernel/label centering improves training and test-time accuracy. The main paper features results of evaluating on centered labels that match the barycenter of the kernel. In Fig. 2 we evaluate on non-aligned kernels and labels as well. Training and evaluating on centered kernels aligned to detection labels produces better scores, possibly because the typically non-centered kernels are offset relative to the training bounding boxes.

![Graph comparing different training and evaluation strategies](image1.png)

Figure 2. Comparison of different training and evaluation strategies. Results are averaged across the blur types $P_{1-3}$. Evaluating and training on kernels aligned to detection labels (Standard Augmentation and centered labels) scores best.

3. Expanded Labels and What the Network Outputs

Fig. 3 shows an example image with motion blur, and the output from both the Standard Augmented and the Expanded Augmented networks. The Expanded augmented network learns to predict bounding boxes that capture the superset of all spatial locations an object occupied during an exposure. This seems to be an easier objective for the network to learn. While one could argue that downstream tasks may prefer original-sized bounding boxes as shown computed by the Standard Augmented model, there is no good compromise there: the middle of the blurred object could be a “stale” image-space location compared to where the object is at the end of the exposure, in, *e.g.* a tracking-by-detection task.

![Example images](image2.png)

Figure 3. Left: Groundtruth image with COCO labels. Middle: Network output from the Standard Augment network. Right: Network output from the Expanded Augment network. Expanded augment networks learn to output boxes that represent the superset of all locations an object has been at during an exposure.
4. Minibatch Normalization as Schneider et al. [39]

In this late-breaking NeurIPS 2020 paper, results are reported for minibatch normalization on networks already trained with augmentation for blurry images. As per their algorithm, we perform minibatch normalization by finding the statistics of the activations of an input example, $\mu$ and $\sigma$, and computing a weighted sum with the training statistics using $N = 16$ and $n = 1$. This is done progressively in one forward pass. In Fig. 4, results are reported for the performance of the original model with this modification. We also experimented with finding an accurate estimate of the target distribution for blurry images by running a large portion of the train set under a specific type of blur and exposure as many times as there are batchnorm layers in the network with $n = 2048$, and using that as normalization statistics, but this did not constitute an improvement. Despite the appeal of this test-time approach, object detection was not substantially better off with it, so we excluded it from our final model.

Figure 4. Comparison of using minibatch normalization on both the original network and blur augmented networks. For only this graph: solid lines are evaluation runs on expanded labels and dashed lines are evaluated on standard labels; the exception here is the original model which is evaluated on expanded labels. Results are averaged across $P_1 - 3$.

5. Qualitative Results

We include a supplementary video with qualitative results and a visual explanation of our method. It can be found here: https://www.youtube.com/watch?v=nNEN-hc2eho.

There, we show real world examples where our model, based on the two proposed remedies, manages to detect objects in many places where the original model fails, especially when the ratio of camera motion to object size is high. Following on from the quantitative experiments in the paper and here, we synthesize blurry COCO images (in the same spirit as [27, 15]) and show sample results in the video.

6. Results Tables

Table 1 and Table 2 contain the raw results used to generate Fig. 6 and Fig. 7 in the paper.
| Variant                                      | Clean  | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ |
|----------------------------------------------|--------|-------|-------|-------|-------|-------|
| Original                                     | 58.50  | 51.12 | 35.40 | 28.93 | 19.17 | 15.76 |
| Standard Augmented                           | 56.51  | 55.00 | 52.37 | 49.51 | 44.02 | 40.91 |
| Deblur then Original                         | 55.50  | 49.67 | 42.90 | 35.02 | 22.34 | 17.07 |
| Deblur then Standard Augmented               | 53.90  | 51.66 | 48.68 | 42.85 | 33.76 | 29.50 |
| Squint                                       | 55.65  | 54.24 | 51.56 | 49.00 | 43.71 | 40.25 |
| AugMix (Non Expanded)                        | 59.34  | 53.27 | 40.62 | 35.19 | 26.82 | 24.61 |
| AugMix PixelLevel                            | 58.93  | 51.89 | 35.13 | 29.11 | 18.81 | 16.41 |
| Original w/ MiniBatch, N = 16, n = 1         | 52.10  | 46.69 | 32.27 | 26.51 | 16.25 | 12.70 |
| Standard Augmented w/ MiniBatch, N = 16, n = 1 | 48.60  | 47.66 | 44.52 | 41.46 | 35.20 | 31.35 |
| Spec By Type                                 | 56.50  | 55.44 | 53.18 | 51.12 | 45.91 | 42.85 |
| Spec By Exposure (Ours)                      | 58.55  | 56.54 | 54.25 | 50.18 | 45.90 | 43.77 |

| Variant                                      | Clean  | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ |
|----------------------------------------------|--------|-------|-------|-------|-------|-------|
| Original                                     | 58.50  | 50.95 | 32.59 | 15.75 | 8.75  | 4.58  |
| Standard Augmented                           | 56.51  | 54.93 | 52.44 | 46.85 | 37.56 | 31.37 |
| Deblur then Original                         | 55.50  | 49.18 | 42.13 | 30.31 | 12.72 | 6.26  |
| Deblur then Standard Augmented               | 53.90  | 51.47 | 48.44 | 40.35 | 23.85 | 15.86 |
| Squint                                       | 55.65  | 54.30 | 51.76 | 46.21 | 37.24 | 31.39 |
| AugMix (Non Expanded)                        | 59.34  | 53.13 | 38.07 | 20.70 | 13.63 | 8.21  |
| AugMix PixelLevel                            | 58.93  | 51.68 | 32.10 | 14.84 | 9.12  | 4.48  |
| Original w/ MiniBatch, N = 16, n = 1         | 52.10  | 46.53 | 31.25 | 16.10 | 8.86  | 4.40  |
| Standard Augmented w/ MiniBatch, N = 16, n = 1 | 48.60  | 47.70 | 44.25 | 37.79 | 27.84 | 20.92 |
| Spec By Type                                 | 56.50  | 55.39 | 52.33 | 47.78 | 39.81 | 33.84 |
| Spec By Exposure (Ours)                      | 58.55  | 56.57 | 53.83 | 47.83 | 40.26 | 35.97 |

| Variant                                      | Clean  | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ |
|----------------------------------------------|--------|-------|-------|-------|-------|-------|
| Original                                     | 58.50  | 50.98 | 32.41 | 14.84 | 2.68  | 0.01  |
| Standard Augmented                           | 56.51  | 55.03 | 52.19 | 46.45 | 33.72 | 20.74 |
| Deblur then Original                         | 55.50  | 49.46 | 41.85 | 29.45 | 7.23  | 1.11  |
| Deblur then Standard Augmented               | 53.90  | 51.59 | 48.00 | 39.53 | 18.47 | 6.38  |
| Squint                                       | 55.65  | 54.24 | 51.39 | 46.03 | 33.54 | 21.48 |
| AugMix (Non Expanded)                        | 59.34  | 52.93 | 38.08 | 19.91 | 4.17  | 0.01  |
| AugMix PixelLevel                            | 58.93  | 51.54 | 32.07 | 14.05 | 2.36  | 0.00  |
| Original w/ MiniBatch, N = 16, n = 1         | 52.10  | 46.67 | 31.48 | 15.77 | 3.13  | 0.01  |
| Standard Augmented w/ MiniBatch, N = 16, n = 1 | 48.60  | 47.80 | 44.10 | 37.17 | 22.23 | 9.81  |
| Spec By Type                                 | 56.50  | 55.36 | 51.70 | 47.00 | 36.81 | 25.66 |
| Spec By Exposure (Ours)                      | 58.55  | 56.55 | 53.68 | 47.66 | 36.93 | 30.44 |

Table 1. Raw numbers from Fig. 6 in the paper. Non-expanded labels used during evaluation. Results are on the COCO minival set under different blur parameters and exposure. From top to bottom, the blur type changes from $P_1$ to $P_2$ to $P_3$. Networks trained with blur augmentation would be trained on non-expanded labels.
| Variant                                      | Clean | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ |
|---------------------------------------------|-------|-------|-------|-------|-------|-------|
| Original                                    | 58.50 | 51.62 | 35.87 | 29.32 | 19.61 | 15.79 |
| Expanded Labels                             | 56.65 | 56.57 | 54.81 | 52.93 | 48.92 | 45.68 |
| Deblur then Original                        | 55.50 | 49.89 | 42.07 | 33.28 | 20.98 | 16.07 |
| Squint Expanded Labels                       | 56.15 | 56.29 | 54.57 | 52.35 | 48.36 | 45.61 |
| AugMix Expanded Labels                       | 51.80 | 46.96 | 36.60 | 31.28 | 22.95 | 21.02 |
| AugMix PixelLevel                            | **58.93** | 51.62 | 35.87 | 29.32 | 19.61 | 15.79 |
| Original w/ MiniBatch, $N = 16$, $n = 1$    | 52.10 | 47.10 | 33.26 | 27.26 | 17.09 | 13.90 |
| Expanded Labels w/ MiniBatch, $N = 16$, $n = 1$ | 47.20 | 45.41 | 40.29 | 35.28 | 27.39 | 23.80 |
| Expanded Labels w/ NonSpatial Augmix        | 58.90 | 56.05 | 54.32 | 52.39 | 48.36 | 45.40 |
| Spec By Type Expanded Labels                | 56.70 | 57.29 | 55.81 | 50.53 | 48.07 |
| Spec By Exposure Expanded Labels (Our Best) | 58.62 | **58.08** | **56.60** | 53.20 |
| Spec By Exposure Expanded Labels (Our Best) | 58.62 | **58.08** | **56.60** | 53.20 | **50.86** | **49.54** |

| Variant                                      | Clean | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ |
|---------------------------------------------|-------|-------|-------|-------|-------|-------|
| Original                                    | 58.50 | 51.50 | 33.26 | 16.49 | 9.41  | 5.20  |
| Expanded Labels                             | 56.65 | 56.42 | 54.86 | 50.57 | 43.60 | 38.35 |
| Deblur then Original                        | 55.50 | 49.50 | 41.07 | 28.32 | 12.19 | 6.24  |
| Squint Expanded Labels                       | 56.15 | 56.25 | 54.53 | 50.09 | 42.92 | 37.66 |
| AugMix Expanded Labels                       | 51.80 | 46.62 | 34.21 | 18.99 | 11.32 | 6.15  |
| AugMix PixelLevel                            | **58.93** | 51.50 | 33.26 | 16.49 | 9.41  | 0.50  |
| Original w/ MiniBatch, $N = 16$, $n = 1$    | 52.10 | 46.99 | 31.77 | 16.92 | 9.71  | 5.07  |
| Expanded Labels w/ MiniBatch, $N = 16$, $n = 1$ | 47.20 | 45.39 | 39.61 | 30.26 | 20.23 | 13.88 |
| Expanded Labels w/ NonSpatial Augmix        | 58.90 | 55.99 | 54.54 | 50.32 | 43.10 | 37.85 |
| Spec By Type Expanded Labels                | 56.70 | 56.75 | 55.23 | 50.85 | 45.55 | 40.81 |
| Spec By Exposure Expanded Labels (Our Best) | 58.62 | **58.01** | **56.39** | 51.05 | **46.35** | **43.73** |

| Variant                                      | Clean | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ |
|---------------------------------------------|-------|-------|-------|-------|-------|-------|
| Original                                    | 58.50 | 51.50 | 32.88 | 15.54 | 2.91  | 0.01  |
| Expanded Labels                             | 56.65 | 56.19 | 54.42 | 50.29 | 40.09 | 30.11 |
| Deblur then Original                        | 55.50 | 49.79 | 40.63 | 27.60 | 6.80  | 1.13  |
| Squint Expanded Labels                       | 56.15 | 56.14 | 54.28 | 49.98 | 39.29 | 29.50 |
| AugMix Expanded Labels                       | 51.80 | 47.03 | 34.30 | 18.28 | 3.74  | 0.01  |
| AugMix PixelLevel                            | **58.93** | 51.50 | 32.88 | 15.54 | 2.91  | 0.01  |
| Original w/ MiniBatch, $N = 16$, $n = 1$    | 52.10 | 47.27 | 32.09 | 15.60 | 3.51  | 0.01  |
| Expanded Labels w/ MiniBatch, $N = 16$, $n = 1$ | 47.20 | 45.49 | 39.28 | 29.73 | 14.66 | 5.55  |
| Expanded Labels w/ NonSpatial Augmix        | 58.90 | 56.01 | 53.99 | 49.94 | 39.74 | 29.91 |
| Spec By Type Expanded Labels                | 56.70 | 56.90 | 54.96 | **51.29** | 43.65 | 35.83 |
| Spec By Exposure Expanded Labels (Our Best) | 58.62 | **58.06** | **56.22** | 50.97 | **44.12** | **40.63** |

Table 2. Raw numbers from Fig. 7 in the paper. Expanded labels used during evaluation. Results are on the COCO minival set under different blur parameters and exposure. From top to bottom, the blur type changes from $P_1$ to $P_2$ to $P_3$. 