12+ Image Quality Attributes that Impact Computer Vision

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Commonlands LLC

Overview

- Intro
- Types of image quality
- Review image quality metrics and the impact on CV
- Summary

Image quality and computer vision require experts from multiple industries

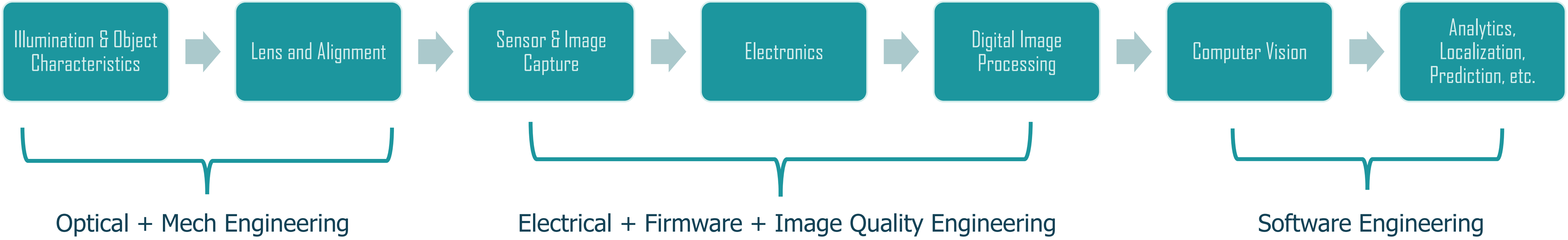

Image quality in the field is fundamental to embedded computer vision performance

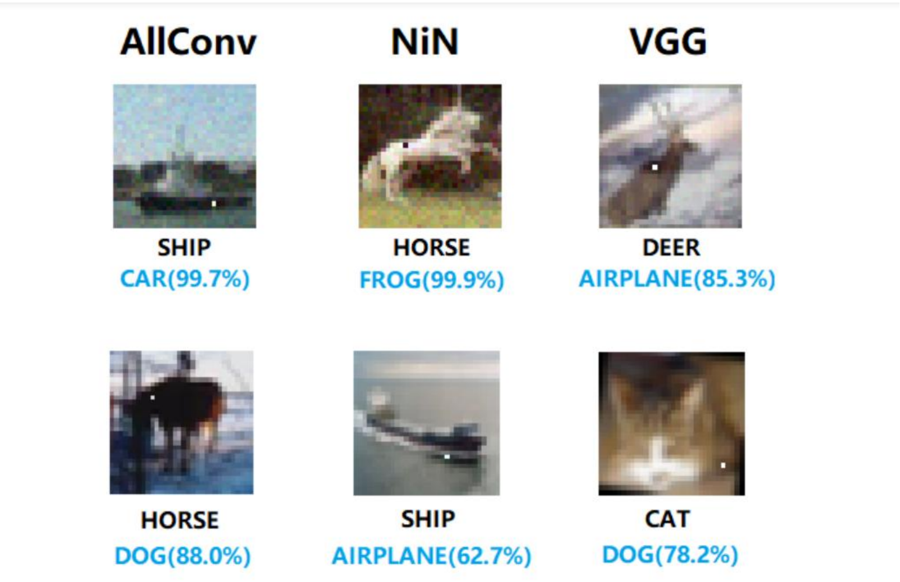

Fig. 1. One-pixel attacks created with the proposed algorithm that successfully fooled three types of DNNs trained on CIFAR-10 dataset: The All convolutional network (AllConv), Network in network (NiN) and VGG. The

Su, et. al. “One Pixel Attack for Fooling Deep Neural Networks”

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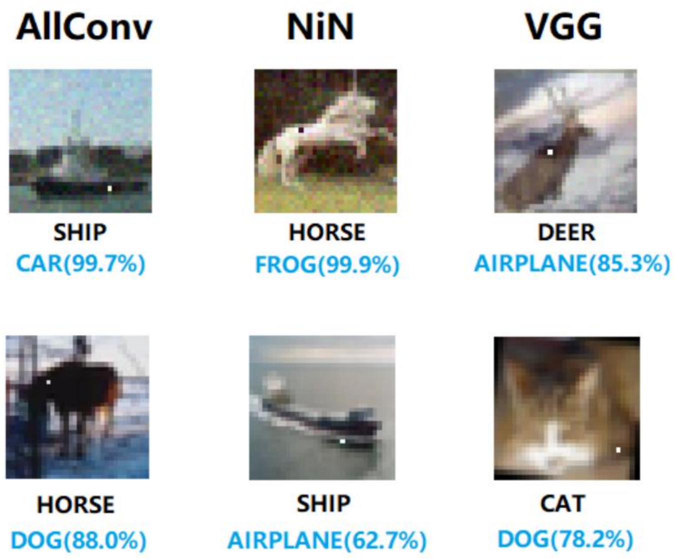

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Su, et. al. "One Pixel Attack for Fooling Deep Neural Networks"

"Nonetheless, we show some examples of situations where nearly imperceptible image modifications can result in dramatic perception changes.

Even in applications without malicious people trying to trick your system, **the natural world may be adversarial enough**."

Pezzementi, et. al "Putting Image Manipulations in Context: Robustness Testing for Safe Perception"

Two types of purpose-based image quality metrics are required to fully characterize an image

Objective

- Independent of preference
- Measurements with image quality test charts

Subjective

- Dependent on preference
- Measurements through focus groups and other user feedback methods

“SNR = 70db” $\stackrel{?}{=}$ “Too Grainy”

“eSFR=20%@100lp/mm” “Too Blurry”

“ΔE=2” $\stackrel{?}{\neq}$ “Not Colorful”

Objective and subjective were coined before modern embedded vision systems

Engineering-Based

- Inputs are related to test charts, camera hardware, and image processing.
- Independent of scene content and human visual quality assessment.

"Objective Image Quality"

Computational-Based

- Inputs are related to human visual cognition such as structure and color.
- Includes content-aware image processing.
- Directly related to image saliency in embedded computer vision.

"Subjective Image Quality"

Reference: Zwanenberg, et. al., 2020, "Edge Detection Techniques for Quantifying Spatial Imaging System Performance and Image Quality"

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Let's investigate how objective image quality metrics could impact your computer vision

1. **Exposure + Motion Blur**
2. Dynamic Range + Artifacts
3. Noise
4. Color
5. Shading
6. Resolution
7. Distortion
8. Texture Blur
9. Stray Light
10. Fringing + Blooming
11. Blemish
12. Dead Pixels

Exposure index combines the scene, lens, exposure length, gain, and image processing

Related KPI

- Exposure Value (EV)

Reference: ISO12232

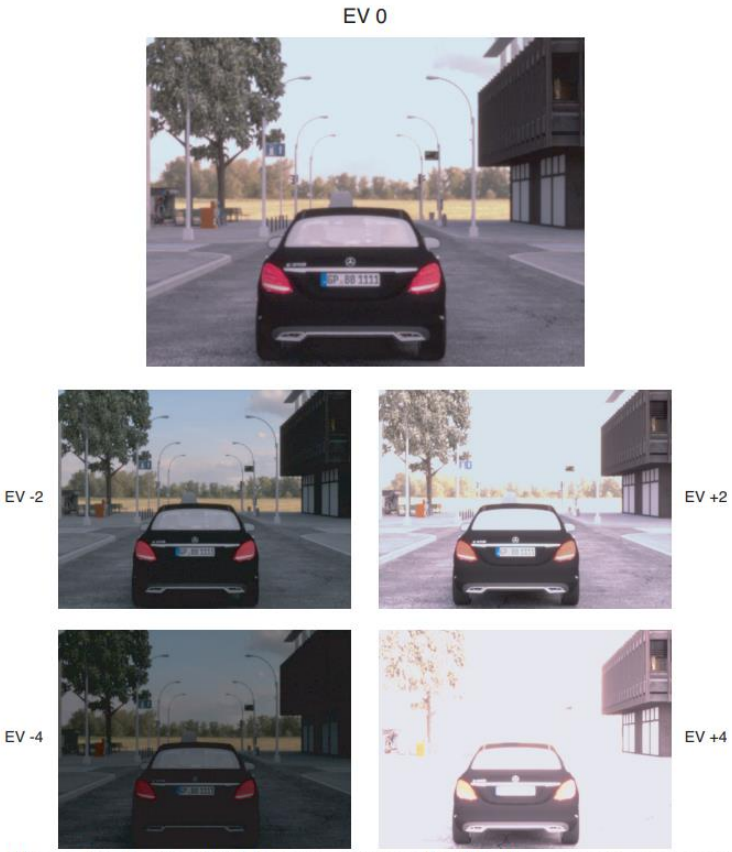
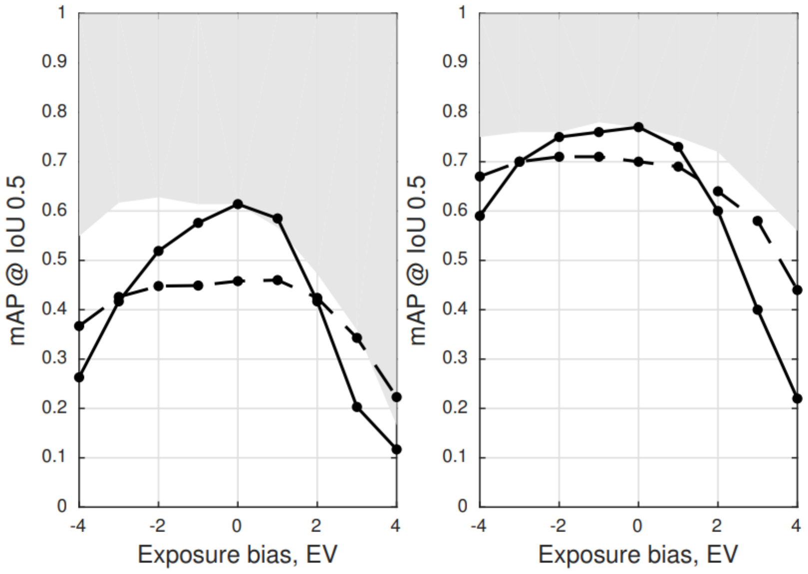


Figure 6: A simulated scene captured with the correct exposure value (top), under-exposed (left), or over-exposed (right).



(a) SSD-Mobilenet (b) RFCN-Resnet101

Figure 7: Network resilience to exposure value bias. The boundary of the shaded region marks the upper bound on accuracy; it is estimated by training and testing the network using sRGB images at each EV bias. The two curves show accuracy when trained at EV = 0 and tested at multiple EV values (solid) or trained at multiple EV values (dashed). The two panels are for the SSD (a) and RFCN (b) networks.

Blasinski, etc. al. "Optimizing Image Acquisition Systems for Autonomous Driving"

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Motion blur is created by long exposure and/or imperfect high-dynamic range recombination

Angular shift

Blur Length

(l, a)	$(0,0)$	$(15,15)$	$(20,20)$	$(25,25)$	$(30,30)$	$(35,35)$	$(40,40)$
$(0,0)$	**81.0**	45.1	31.2	22.6	16.6	13.3	11.2
$(15,15)$	70.8	**72.6**	69.0	59.7	45.3	32.3	23.4
$(20,20)$	67.1	71.5	**69.9**	65.9	57.5	44.7	33.1
$(25,25)$	60.0	67.9	68.2	**66.9**	63.9	57.0	47.3
$(30,30)$	55.4	62.8	64.5	65.0	**64.2**	61.0	55.5
$(35,35)$	47.2	55.4	58.7	61.0	62.3	**61.6**	58.5
$(40,40)$	44.5	47.3	50.6	54.9	58.3	59.8	**59.0**

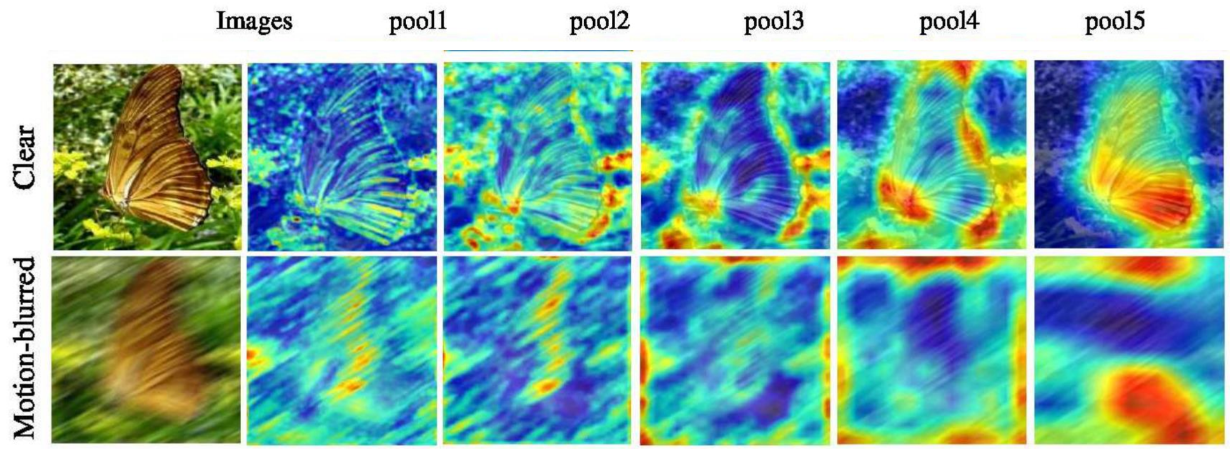

Fig. 5. Activations of hidden layers of CNN on image classification. From left to right are input images, and the activations at $pool_1$, $pool_2$, $pool_3$, $pool_4$, and $pool_5$ layers, respectively.

Pei, et. al. "Effects of Image Degradations to CNN-based Image Classification"

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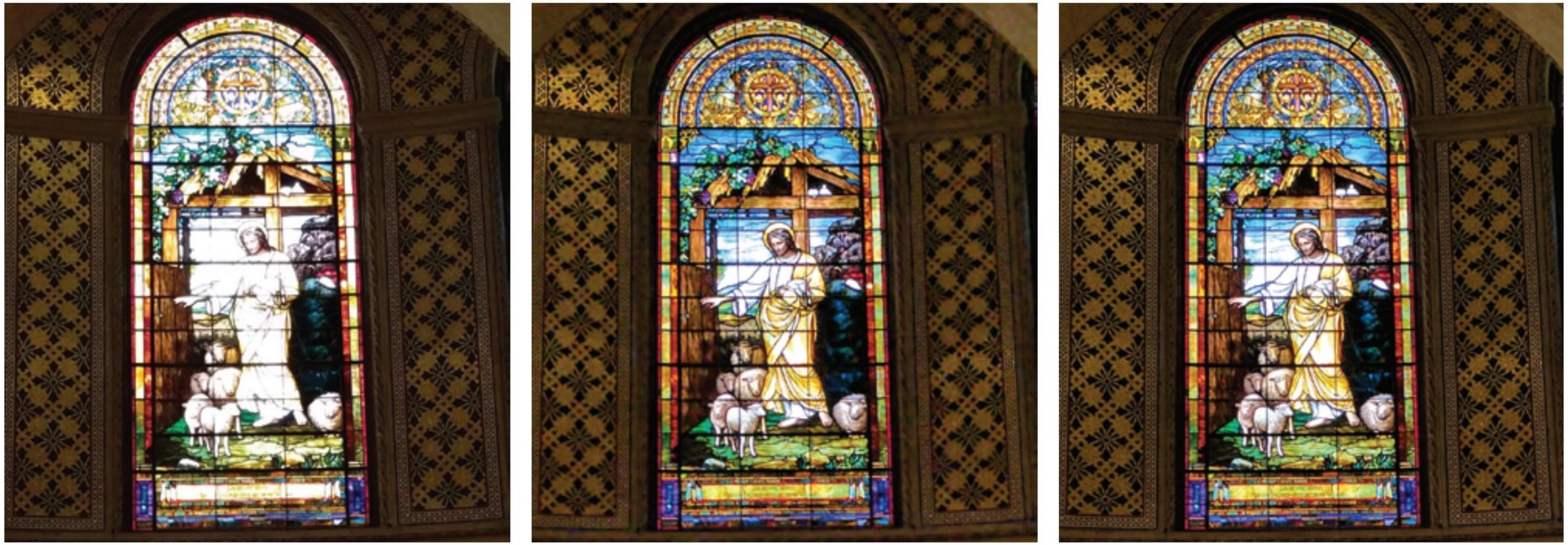
Camera dynamic range is the ratio of maximum to minimum signal, before saturation occurs

Related KPI

- Dynamic Range (dB)

Reference: ISO21550



Hasinoff, et. al. "Burst photography for high dynamic range and low-light imaging on mobile cameras"

Even modern HDR techniques can introduce other image quality artifacts

Figure 2: Common HDR multiplexing artifacts. Crops (a) and (b): ghosting. Crop (c): SNR discontinuity.

Robidoux, et. al. "End-to-end High Dynamic Range Camera Pipeline Optimization"

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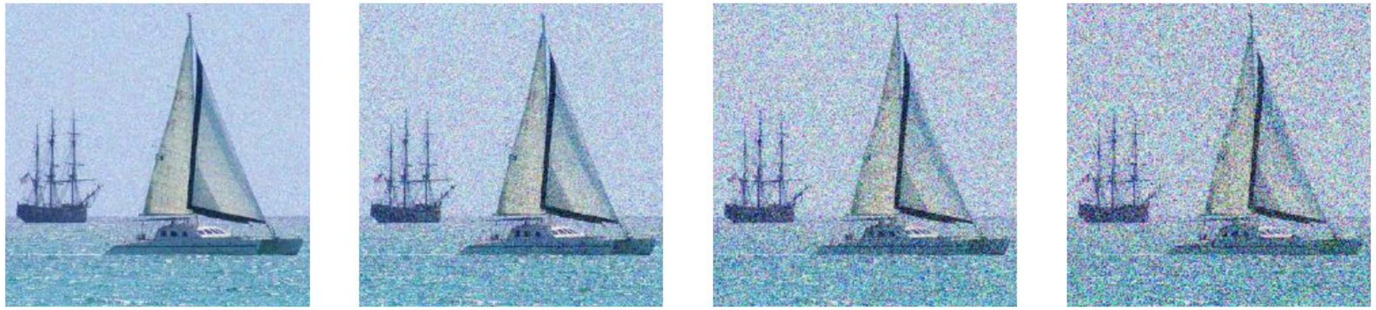
Noise is split into single pixel (temporal /random) and multi-pixel (spatial/pattern)

Related KPIs

- Signal-to-Noise Ratios (multiple types)
- Noise Power Spectrum (Frequency)

Reference: ISO15739



Noise	Caffe	0.439129	0.496755	0.123831	0.00186453
	VGG-CNN-S	0.354262	0.612398	0.444991	0.0499469
	GoogleNet	0.546162	0.287545	0.130923	0.0513721
	VGG16	0.406895	0.336332	0.48098	0.280146

Fig. 3: **Example distorted images.** For each image we also show the output of the soft-max unit for the correct class. This output corresponds to the confidence the network has of the considered class. For all networks and for all distortions this confidence decreases as the image quality decreases.

Dodge, et. al. "Understanding How Image Quality Affects Deep Neural Networks"

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Color can impact edge contrast when using multiple channels and auto-white balance

Related KPI

- ΔE (Color Accuracy)

Reference: ISO17321

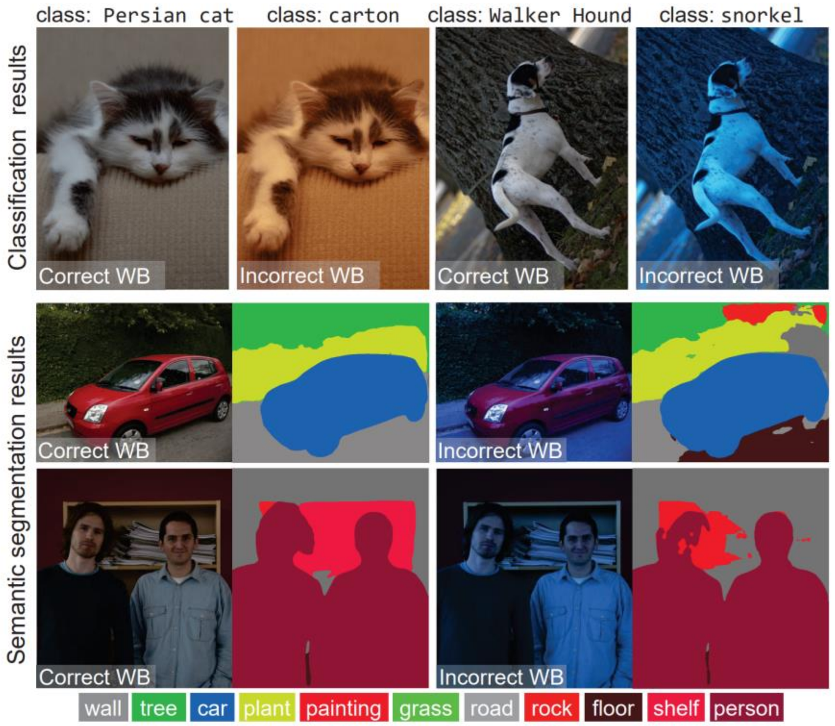


Figure 1. The effect of correct/incorrect computational color constancy (i.e., white balance) on (top) classification results by ResNet [29]; and (bottom) semantic segmentation by RefineNet [39].

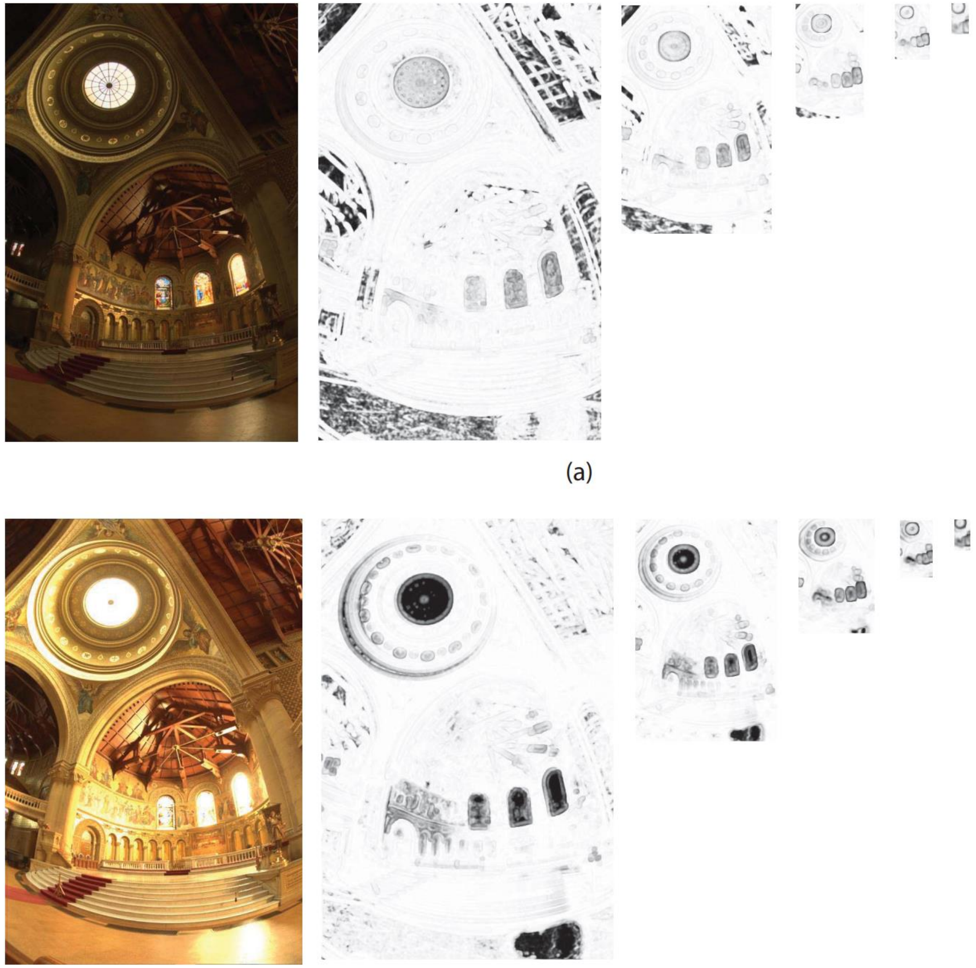
Afifi+Brown. " What Else Can Fool Deep Learning? Addressing Color Constancy Errors on Deep Neural Network Performance

Dynamic range and color are closely related to tone mapping which impacts perception at every scale

Related KPI

- Contrast Detection Probability

Reference: ISO12232



(a)

(b)

Yeganeh, et. al. "Objective Quality Assessment of Tone-Mapped Images"

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Luminance shading changes accuracy from center to edge of the field of view

Related KPIs

- Luminance Non-uniformity
- Lightness non-uniformity

Reference: ISO17957

Marc Levoy, ICCV 2015, "Extreme imaging using cell phones"

Shading can include a radial color shift, impacting CV in different parts of the field

Let's investigate how objective image quality metrics could impact your computer vision

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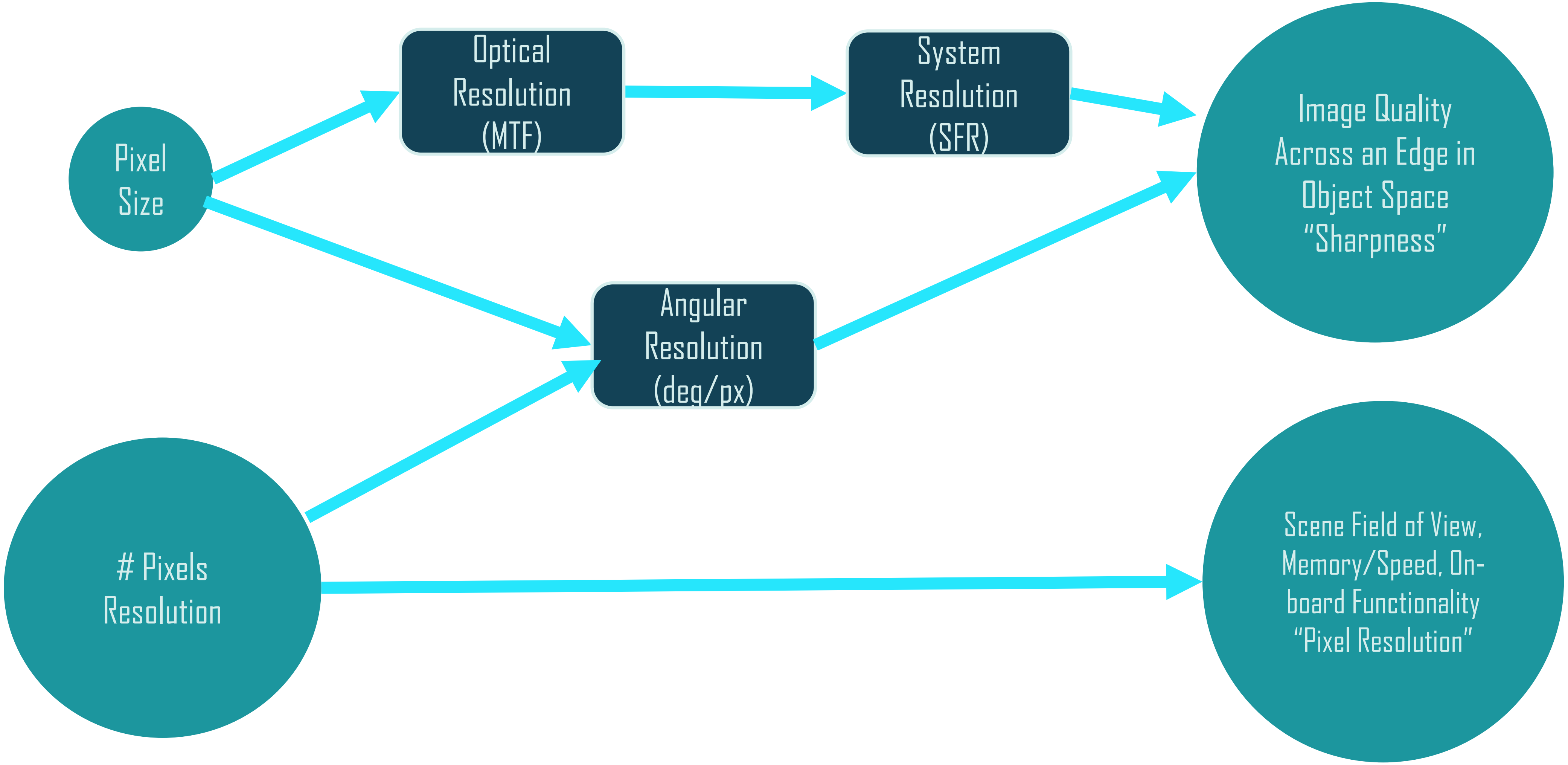
Resolution comes in many flavors



All types of resolution jointly impact the performance of embedded vision systems

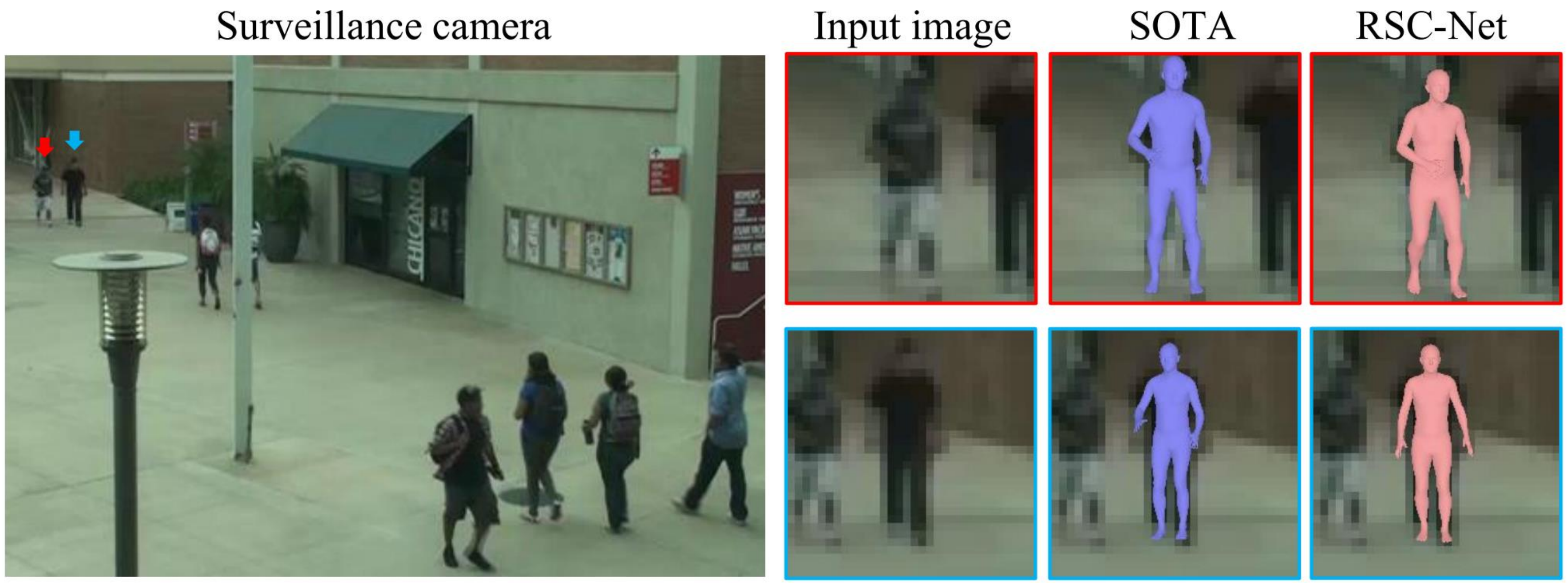


Fig. 1. 3D human shape and pose estimation from a low-resolution image captured from a real surveillance video. SOTA method [25] that works well for high-resolution images performs poorly at low-resolution ones.

SOTA=State of the art as of Q1'20: "SPIN"

Xu, et. al. "3D Human Shape and Pose from a Single Low-Resolution Image with Self-Supervised Learning"

The Spatial Frequency Response (SFR) and contrast sensitivity are a corollary to "blur"

Related KPIs

- Edge SFR (eSFR), sinusoidal SFR (sSFR)
- Lens MTF
- Contrast Sensitivity Function (CSF)
- Contrast Detection Probability (CDP)

Reference: ISO12233, IEEE P2020

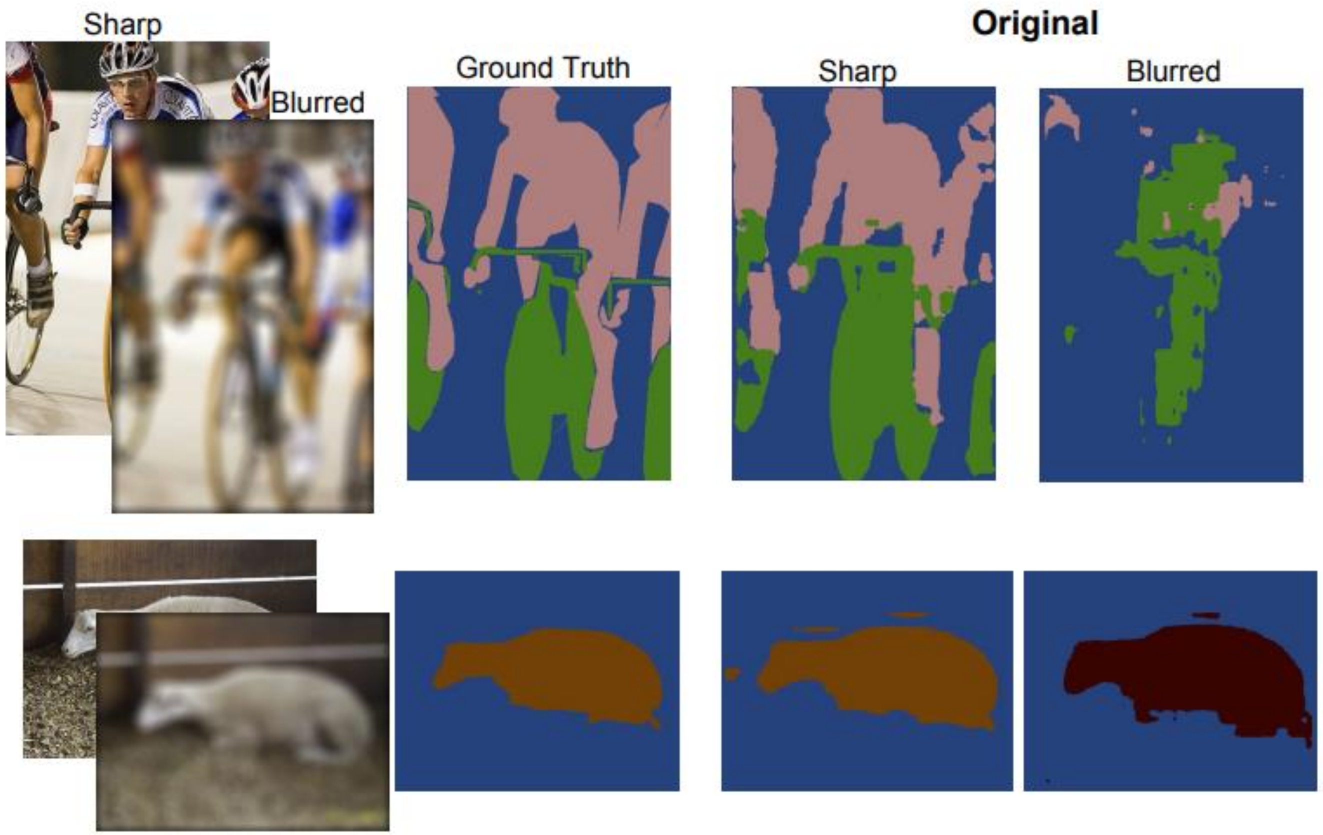


Figure 5. Semantic segmentation results on sharp and blurred images using the Zoo

Vasiljevic, et. Al. "Examining the Impact of Blur on Recognition by Convolutional Networks"

SFR can also characterize 10+ artifacts resulting from image compression quality

Example of Artifacts

- Aliasing
- Ringing
- Blocking

Reference: E. Allen, Thesis: "Image Quality Evaluation in Lossy Compressed Imaged"

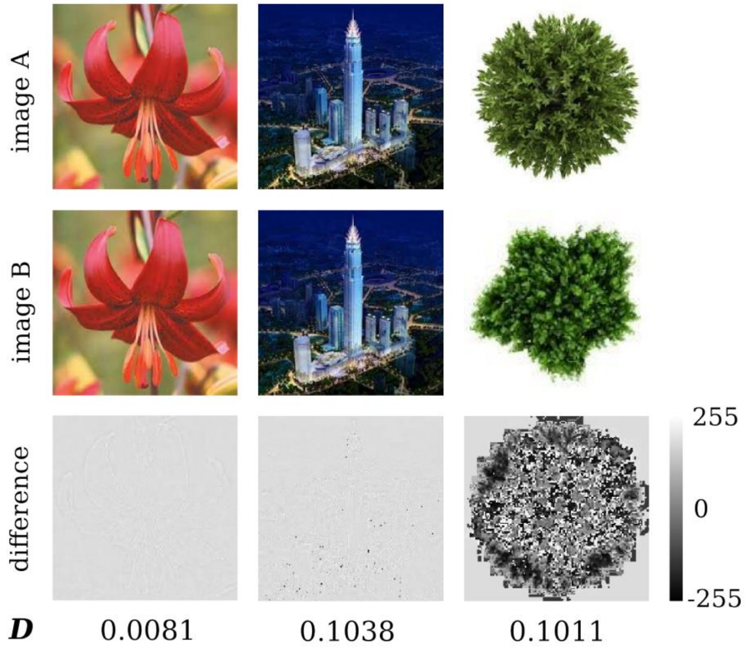


Figure 1: Near-duplicate images can confuse state-of-the-art neural networks due to feature embedding instability. Left and middle columns: near-duplicates with small (left) and large (middle) feature distance. Image A is the original, image B is a JPEG version at quality factor 50. Right column: a pair of dissimilar images. In each column we display the pixel-wise difference of image A and image B, and the feature distance D [13]. Because the feature dis-

Zheng, et. Al " Improving the Robustness of Deep Neural Networks via Stability Training"

Angular resolution defines the # of pixels each object has for feature extraction

Related KPIs

- # Pixels per °
- # Pixels per unit distance across an object

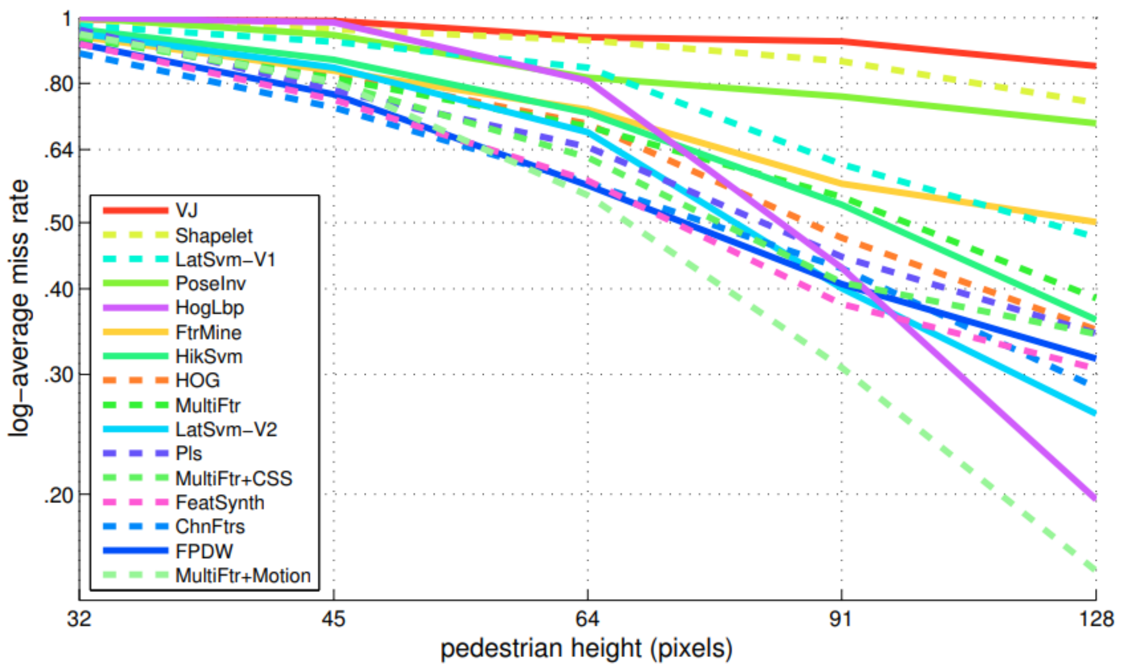


Fig. 12. Performance as a function of scale. All detectors improve rapidly with increasing scale, especially MULTIFTR+MOTION, HOGLBP and LATSVM-V2 which utilize motion, texture and parts, respectively. At small scales state-of-the-art performance has considerable room for improvement.

Dollár, et. al. "Pedestrian Detection: An Evaluation of the State of the Art"

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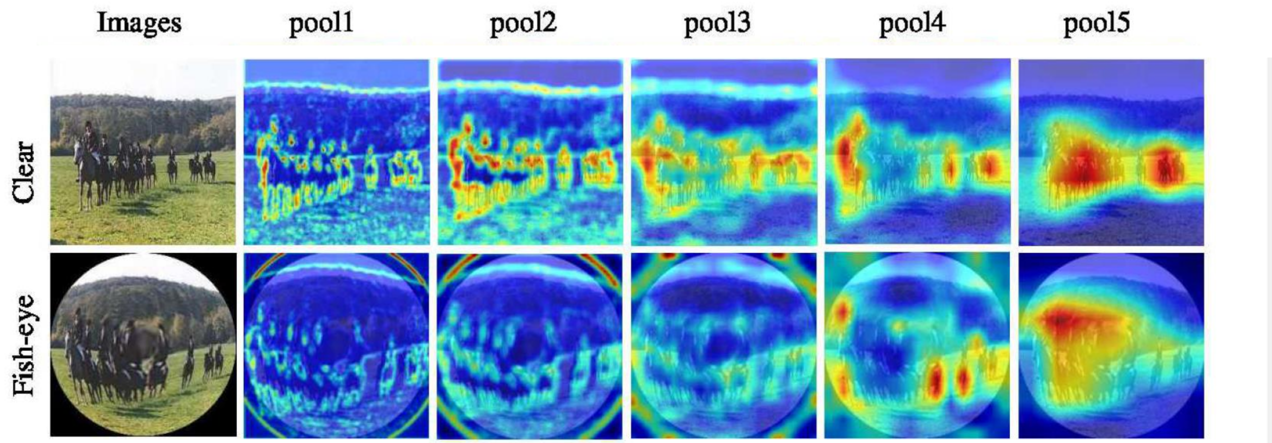
Distortion is the change in angular resolution (magnification) across field

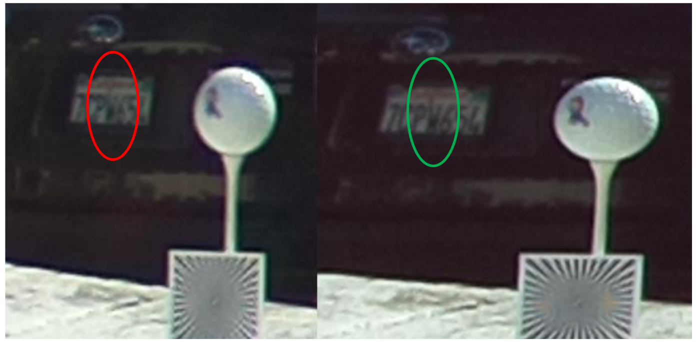
Related KPI

- % Distortion (Optical, TV, SMIA TV)

Reference: ISO17850



Pei, et. al. “Effects of Image Degradations to CNN-based Image Classification”



Angular resolution and perspective distortion at 45° Off Axis

Negative FΘ

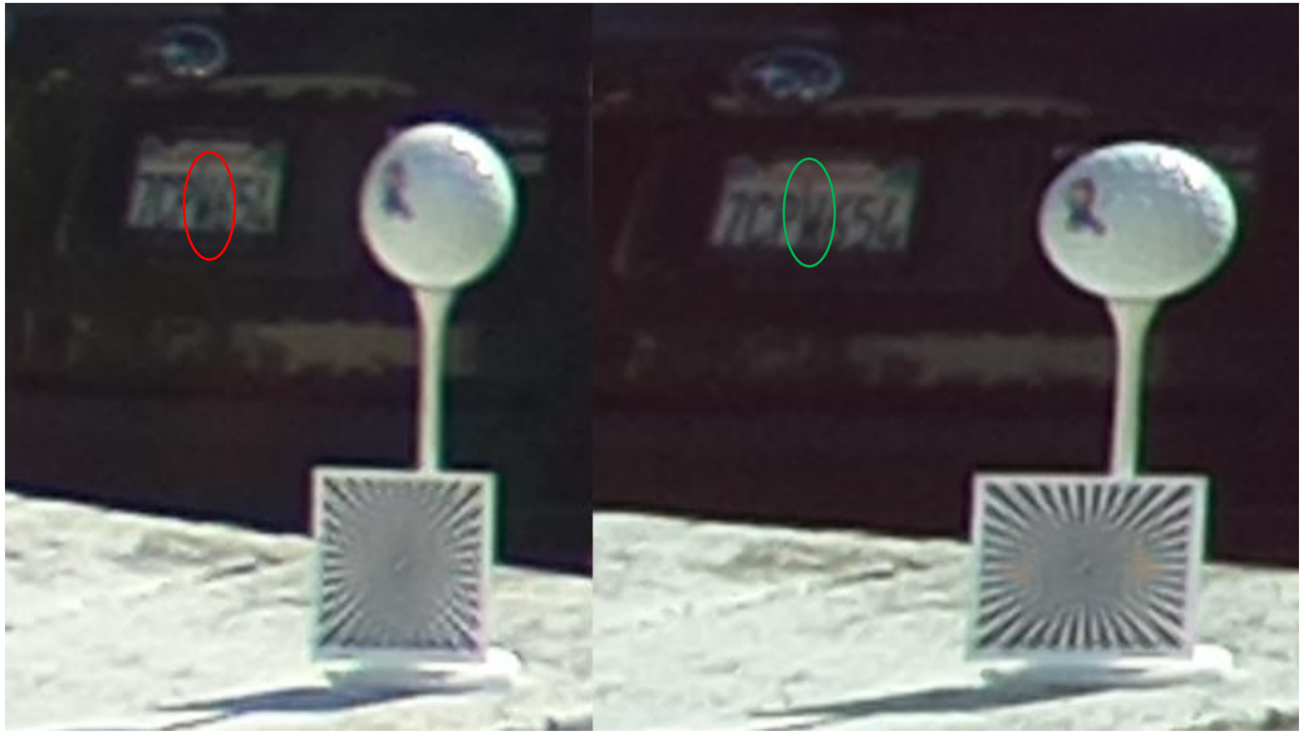
Rectilinear

Distortion is the change in angular resolution (magnification) across field

Related KPI

- % Distortion (Optical, TV, SMIA TV)

Reference: ISO17850



Negative FΘ

Rectilinear

Angular resolution and perspective distortion at 45° Off Axis

Distortion is the change in angular resolution (magnification) across field

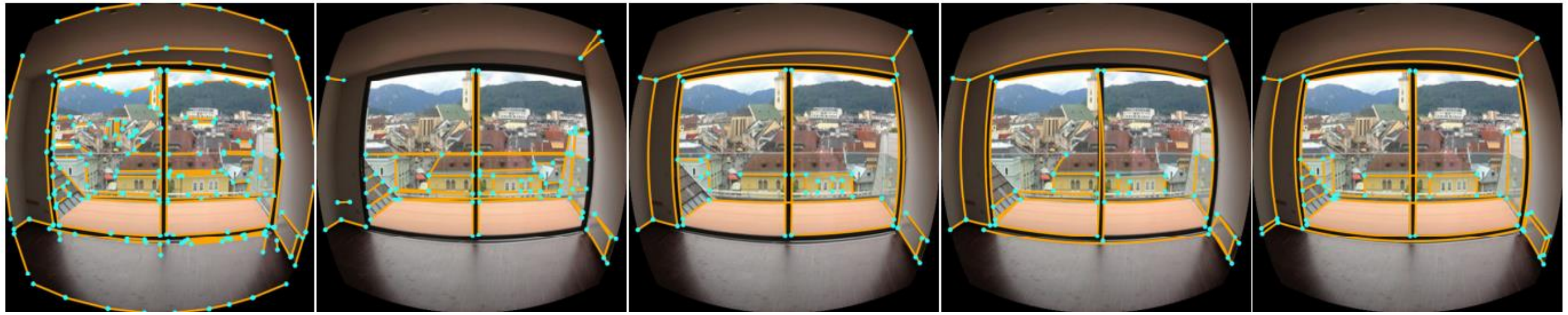
Related KPI

- % Distortion (Optical, TV, SMIA TV)

Reference: ISO17850

Rectilinear

Spherical/Fisheye



LSD [24] | L-CNN [27] | HAWP^{+} [28] | ULSD^{2} (ours) | Ground truth

Li, et.al. 2020, "ULSD: Unified Line Segment Detection across Pinhole, Fisheye, and Spherical Cameras"

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Texture SFR (and loss) results from noise reduction algorithms that filter high frequencies

Related KPI

- Texture SFR

Reference: ISO19567

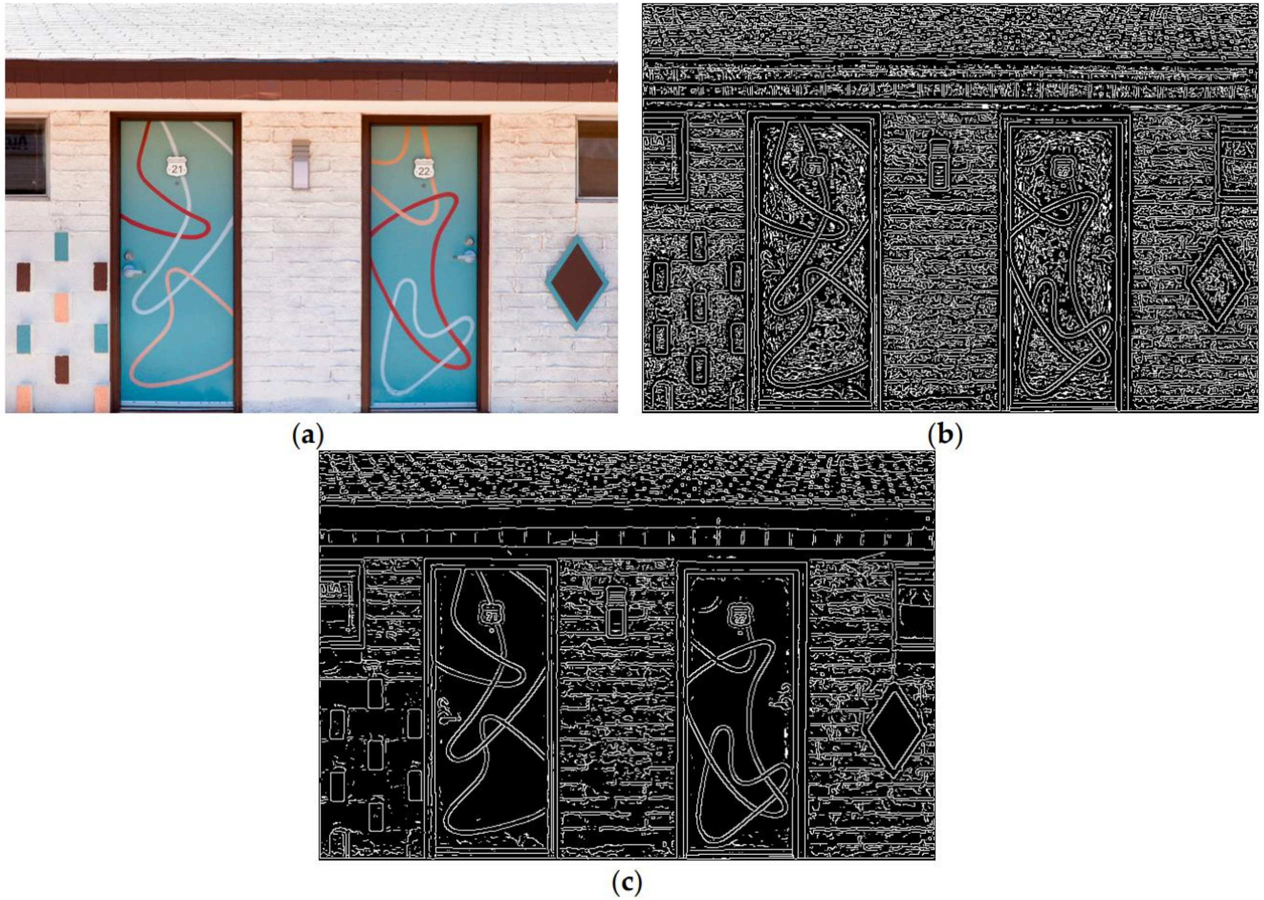

Figure 1. Noise filtering process. (**a**) Original image (640 × 427) [17]; (**b**) gradient change image before noise filtering; (**c**) gradient change image after noise filtering.

Chen, et. Al. “Texture Construction Edge Detection Algorithm”

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Stray light from lenses create regions of low contrast and low detection probability

Related KPIs

- Glare spread function
- Contrast detection probability

Reference: ISO18844

NOTE—Two sequential video frames while entering a tunnel that demonstrate contrast reduction by veiling glare, caused by sunlight illuminated dust particles. In the left image, the effect significantly hinders the recognition of a preceding car while in the right image (only a few milliseconds later) the sunlight is blocked away and a robust detection of the car is possible.

IEEE P2020 Whitepaper

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Chromatic aberration from lenses can result in artifacts around high contrast edges

Related KPIs

- Chromatic Displacement

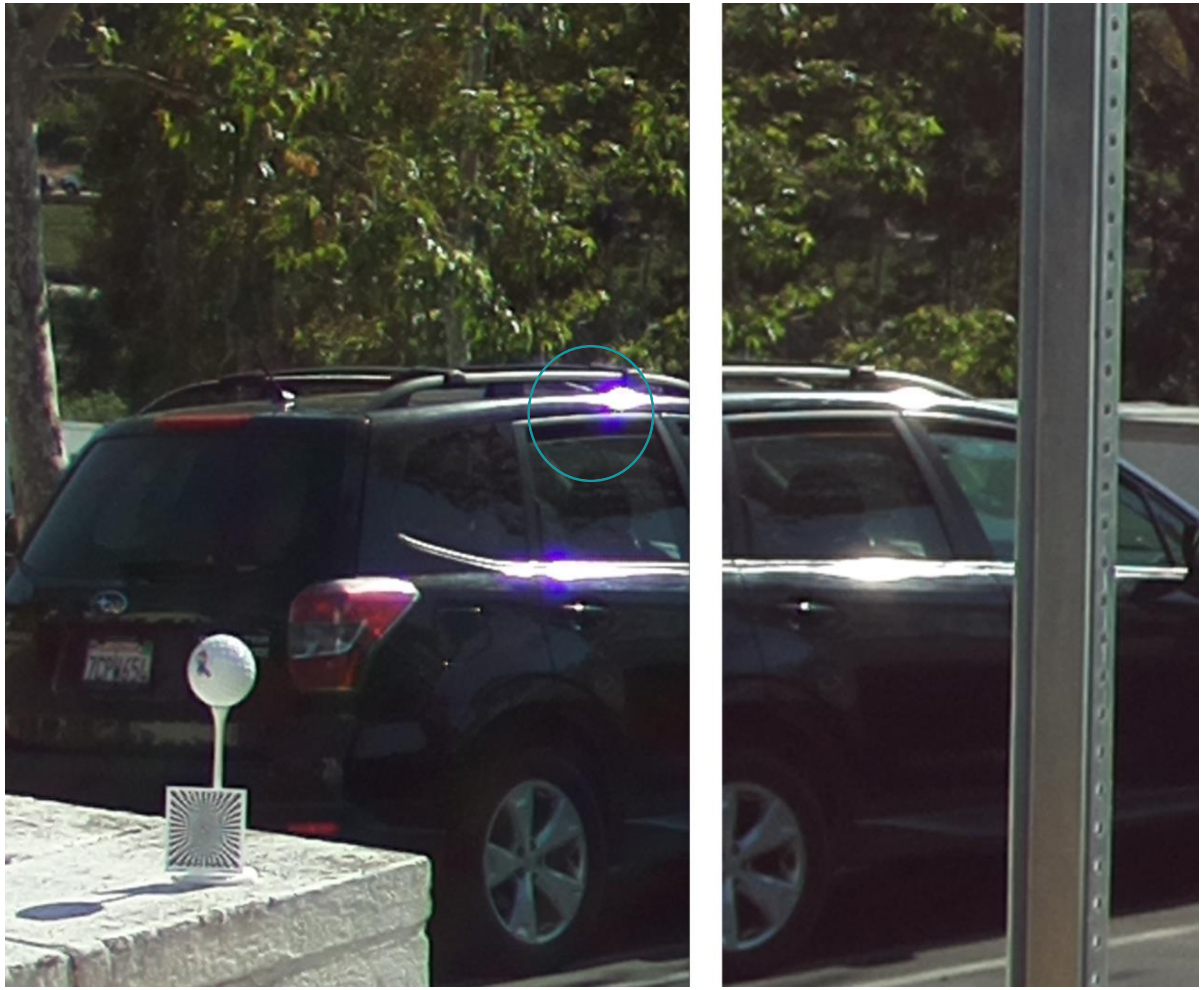
Reference: ISO19084

(a) (b)

Figure 15. Result of correcting the image in Figure 13(b) using parameters recovered from the image in Figure 13(a). (a-b) Close-ups of before and after pairs. The edges in the corrected image appear substantially less reddish. In (b), the residual artifact at the edge of the building is caused by saturation (which our technique cannot handle properly at present).

Kang, "Automatic Removal of Chromatic Aberration from a Single Image"

There are many types of color fringing, some result from blooming/cross-talk in sensor and tuning



Original images

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Image blemishes occur when dust /dirt / moisture are on the sensor or in / on the lens

Related KPIs

- # and size of blemishes

Reference:

https://www.imatest.com/docs/blemish/

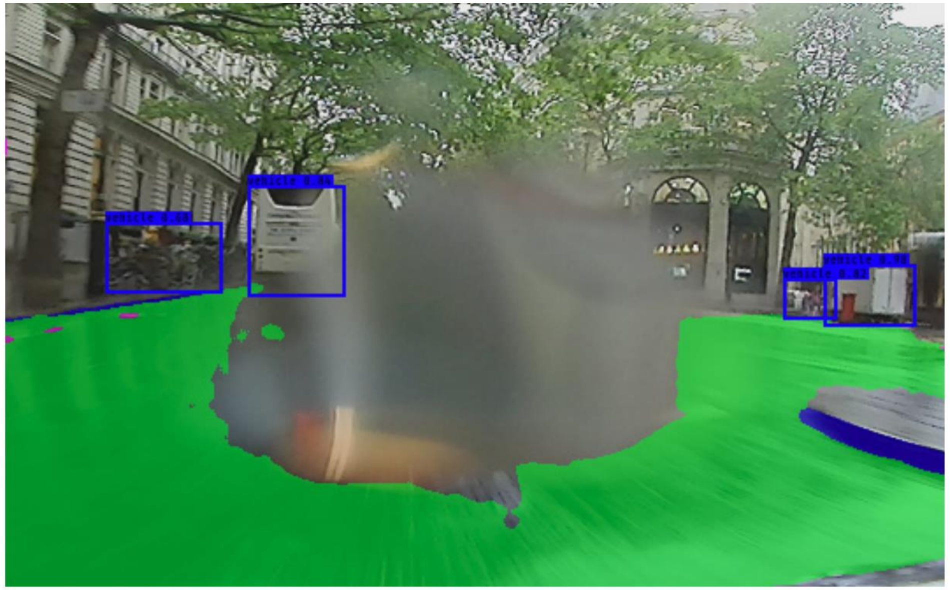

Figure 1: The example of a semi-transparent soiling in form of a water drop on the camera lens. The detection of the bus behind the water drop works still well, while the road segmentation (green) is highly degraded in the soiled region. In

Michal Uricar "Let's Get Dirty: GAN Based Data Augmentation for Camera Lens Soiling Detection in Autonomous Driving."

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Dead pixels brings us full circle, as a real-world adversarial attack if no correction is performed

NiN

HORSE
FROG(99.9%)

Su, et. al. "One Pixel Attack for Fooling Deep Neural Networks"

Dead pixels brings us full circle, as a real-world adversarial attack if no correction is performed

Su, et. al. "One Pixel Attack for Fooling Deep Neural Networks"

"Nonetheless, we show some examples of situations where nearly imperceptible image modifications can result in dramatic perception changes.

Even in applications without malicious people trying to trick your system, **the natural world,** **[your camera hardware, and your image processing pipeline]** **may be adversarial enough**."

Pezzementi, et. al "Putting Image Manipulations in Context: Robustness Testing for Safe Perception"

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Where do I learn more about how image quality influences computer vision?

Visit our website for the slides, the papers cited in this talk, plus related resources:

-> Contact me at max.henkart@commonlands.com if working on a camera HW project or looking for lenses

https://commonlands.com/summit2022

Resources through the Alliance

- Felix Heide, Embedded Vision Summit 2018:
  - https://www.edge-ai-vision.com/2018/08/understanding-real-world-imaging-challenges-for-adas-and-autonomous-vision-systems-ieee-p2020-a-presentation-from-algolux/

Notable examples included on our reference page:

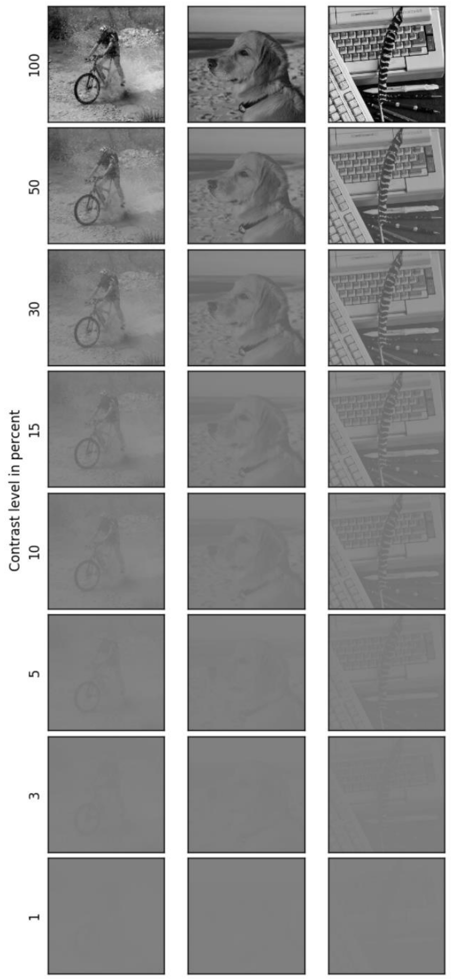
IEEE P2020 Automotive Image Quality (Computer Vision) White Paper

Electronic Imaging (January 2023) and Imaging.org

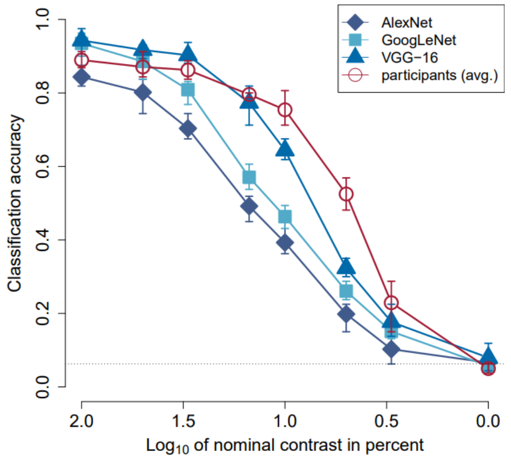
University of Westminster & Nvidia's Collaboration on Image Quality Metrics

Backup Slides

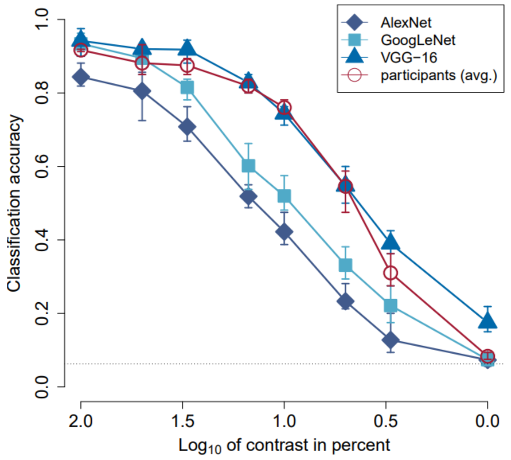
Contrast loss impacts both human visual perception and CNN-based methods.



(a) Contrast-experiment stimuli



(a) Contrast-experiment accuracy for JPEG images



(b) Contrast-experiment accuracy for PNG images

Geirhos, et. al. "Comparing deep neural networks against humans: object recognition when the signal gets weaker"

Quantitative Degradation of Agricultural Outdoor Detection Based on Image Quality

Mutator & Parameters	MS-CNN	SSD w/ MobileNets	SSD w/ Inception	Faster R-CNN w/ Resnet 101	R-FCN w/ Resnet 101	Faster R-CNN w/ Inception Resnet	Deformable R-FCN	Deformable Faster R-CNN
Baseline	**0.60**	**0.29**	**0.22**	**0.64**	**0.64**	**0.71**	**0.71**	**0.73**
Defocus (u_f 10.0; κ 2.0)	0.59	0.29	0.22	0.64	0.63	0.71	0.63	0.73
Defocus (u_f 5.0; κ 2.0)	0.59	0.29	0.22	0.64	0.64	0.71	0.63	0.73
Defocus (u_f 2.0; κ 2.0)	0.52	0.29	0.24	0.63	0.63	0.68	0.62	0.74
Defocus (u_f 1.0; κ 2.0)	0.38	0.20	0.21	0.54	0.53	0.57	0.50	0.69
Defocus (u_f 10; κ 2.8)	0.59	0.29	0.22	0.64	0.63	0.71	0.63	0.73
Defocus (u_f 5; κ 2.8)	0.59	0.29	0.23	0.64	0.64	0.71	0.63	0.73
Defocus (u_f 2; κ 2.8)	0.47	0.26	0.23	0.59	0.59	0.65	0.58	0.73
Defocus (u_f 1.0; κ 2.8)	0.27	0.14	0.17	0.47	0.44	0.44	0.40	0.58
Defocus (u_f 10.0; κ 3.6)	0.59	0.29	0.22	0.64	0.63	0.71	0.63	0.73
Defocus (u_f 5.0; κ 3.6)	0.57	0.29	0.23	0.64	0.63	0.70	0.62	0.73
Defocus (u_f 2.0; κ 3.6)	0.43	0.24	0.22	0.55	0.56	0.60	0.53	0.70
Defocus (u_f 1.0; κ 3.6)	0.19	0.11	0.13	0.42	0.38	0.36	0.34	0.51
Gaussian Blur (σ 0.5)	0.56	0.29	0.23	0.64	0.64	0.70	0.63	0.74
Gaussian Blur (σ 1.0)	0.48	0.27	0.24	0.61	0.61	0.67	0.60	0.74
Gaussian Blur (σ 1.5)	0.41	0.22	0.22	0.56	0.56	0.61	0.54	0.71
Gaussian Blur (σ 2.0)	0.33	0.17	0.19	0.51	0.49	0.53	0.47	0.65
Gaussian Blur (σ 2.5)	0.25	0.13	0.16	0.47	0.44	0.45	0.41	0.59
Gaussian Blur (σ 3.0)	0.19	0.10	0.14	0.43	0.40	0.37	0.35	0.53
Haze (u_V 978.0 m (β 0.004))	0.56	0.29	0.22	0.64	0.64	0.69	0.63	0.73
Haze (u_V 326.0 m (β 0.012))	0.50	0.28	0.21	0.64	0.65	0.67	0.63	0.73
Haze (u_V 97.8 m (β 0.04))	0.36	0.19	0.14	0.61	0.60	0.61	0.61	0.71
Alpha Blend (α 0.1)	0.53	0.29	0.21	0.64	0.64	0.69	0.63	0.73
Alpha Blend (α 0.25)	0.38	0.24	0.18	0.64	0.62	0.66	0.63	0.73
Alpha Blend (α 0.5)	0.22	0.05	0.09	0.63	0.55	0.63	0.63	0.72
Alpha Blend (α 0.75)	0.21	0.00	0.00	0.54	0.28	0.55	0.59	0.67
JPEG Compression (q 40)	0.56	0.27	0.21	0.62	0.61	0.68	0.61	0.71
JPEG Compression (q 20)	0.51	0.25	0.19	0.57	0.57	0.64	0.58	0.68
JPEG Compression (q 10)	0.39	0.19	0.15	0.47	0.46	0.51	0.49	0.58
Brightness (b 2.00)	0.61	0.14	0.09	0.51	0.59	0.60	0.59	0.66
Brightness (b 1.33)	0.63	0.25	0.16	0.60	0.64	0.66	0.63	0.72
Brightness (b 1.14)	0.61	0.27	0.19	0.62	0.64	0.69	0.63	0.73
Brightness (b 0.88)	0.57	0.30	0.25	0.65	0.63	0.72	0.62	0.73
Brightness (b 0.75)	0.55	0.30	0.26	0.64	0.62	0.73	0.62	0.72
Brightness (b 0.50)	0.56	0.24	0.23	0.61	0.58	0.73	0.60	0.71
Salt and Pepper (1% of pixels)	0.58	0.27	0.20	0.60	0.61	0.66	0.61	0.70
Salt and Pepper (2% of pixels)	0.55	0.25	0.18	0.57	0.59	0.63	0.60	0.68
Salt and Pepper (5% of pixels)	0.50	0.21	0.14	0.51	0.54	0.58	0.55	0.61
Drop Channel Cb (YCbCr)	0.36	0.01	0.00	0.40	0.09	0.41	0.16	0.11
Drop Channel Cr (YCbCr)	0.30	0.00	0.00	0.33	0.04	0.49	0.13	0.10
Drop Channel R (RGB)	0.64	0.07	0.01	0.51	0.34	0.56	0.34	0.37
Drop Channel G (RGB)	0.49	0.03	0.00	0.45	0.23	0.60	0.28	0.32
Drop Channel B (RGB)	0.40	0.03	0.03	0.39	0.23	0.58	0.29	0.29
Additive (ζ_w 5.0; ζ_u 0.5; ψ 0.5)	0.60	0.28	0.21	0.63	0.62	0.69	0.62	0.71
Additive (ζ_w 5.0; ζ_u 0.5; ψ 0.7)	0.60	0.27	0.19	0.61	0.60	0.66	0.60	0.68
Additive (ζ_w 5.0; ζ_u 1.5; ψ 0.5)	0.60	0.26	0.19	0.61	0.59	0.65	0.59	0.66
Additive (ζ_w 15.0; ζ_u 0.5; ψ 0.5)	0.59	0.25	0.18	0.60	0.58	0.65	0.59	0.66
Additive (ζ_w 5.0; ζ_u 2.5; ψ 0.5)	0.59	0.21	0.15	0.56	0.54	0.60	0.55	0.60

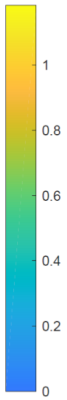


TABLE IV: ADRs for each SUT under all mutations. Numerical values show ADR, while cell colorization depicts ADR normalized relative to that SUT's baseline score, to highlight robustness characteristics. The color bar at right shows the normalized scale's color mapping; note that performance can sometimes improve over baseline.

Pezzementi, et. al. "Putting Image Manipulations in Context: Robustness Testing for Safe Perception"

- ADR= Average Detection Rate

Quantitative Degradation of Facial Recognition Networks Based on Image Quality

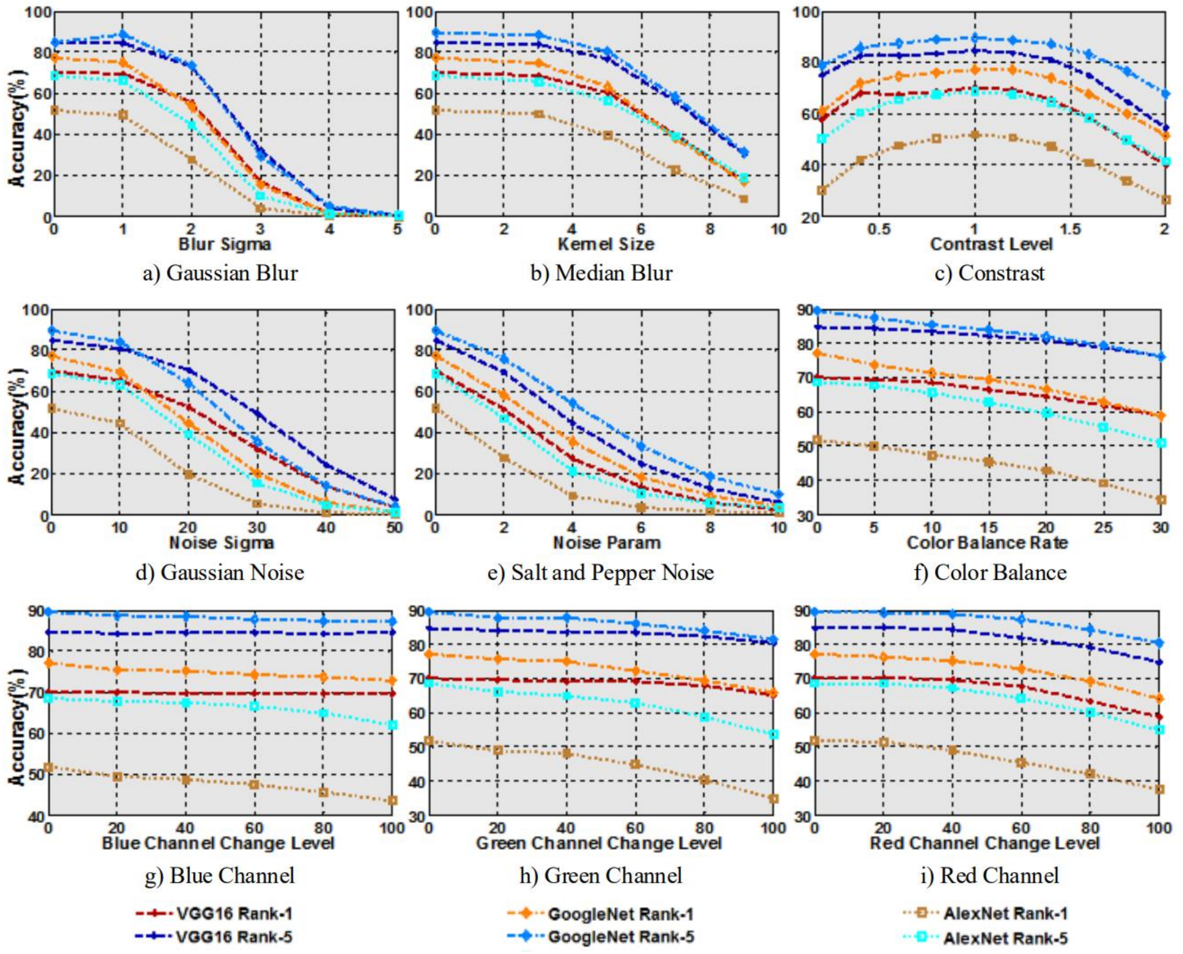


Fig. 3: Rank-1 and Rank-5 performances of different deep CNN-based face representation under image degradations.

Karahan, et. al. "How Image Degradations Affect Deep CNN-based Face Recognition?"

Quantitative Degradation of A Variety of Images and Datasets

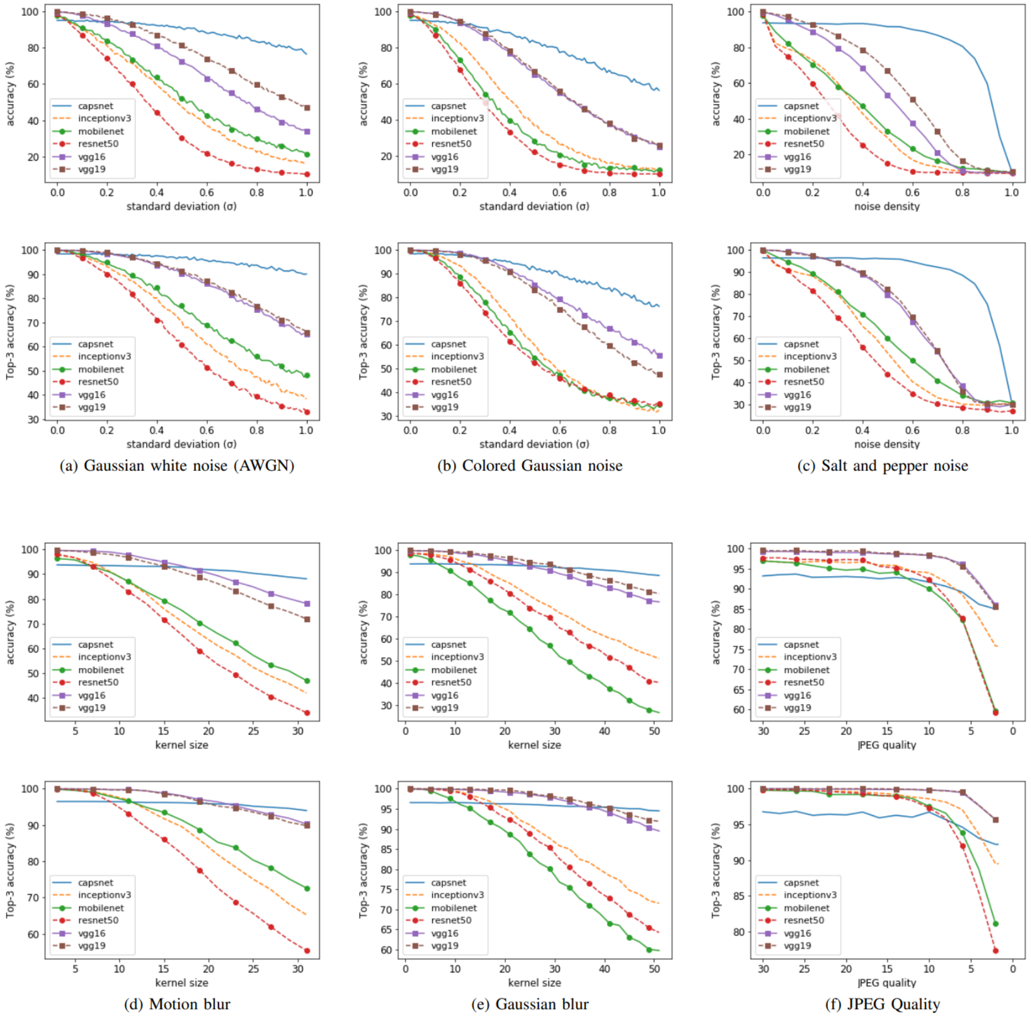


Fig. 3. Comparison of classification accuracies of different CNN architectures under different image degradations on synthetic digits dataset. For each type of degradation, the top figure shows accuracy (top-1 accuracy) vs. respective degradation parameter and the bottom figure shows top-3 accuracy vs. respective degradation parameter.

Roy, et. Al. "Effects of Degradations on Deep Neural Network Architectures"

6) Distortion is the change in angular resolution (magnification) across field

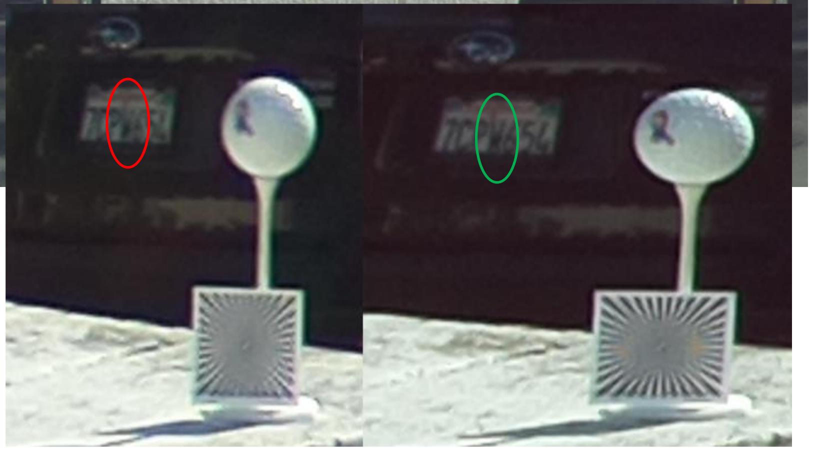
Example of CV impact

- Must select line detection and/or dewarping methods carefully as camera to camera variations can throw off Hough transfroms and RANSAC
- Fewer pixels for detection tasks at edges of negative FΘ lenses

KPI

- % Distortion (Optical, TV, SMIA TV)

Reference: ISO17850



Two 90° HFoV lenses on IMX477.
Left 10% of image is shown.

Original Images

Commonlands
Cameras & Optics