

NIST IR 8485 DRAFT SUPPLEMENT

**Face Analysis Technology Evaluation
(FATE) Part 11: Face Image Quality
Vector Assessment**
Specific Image Defect Detection

Joyce Yang
Patrick Grother
Mei Ngan
Kayee Hanaoka
Austin Hom

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**NIST Internal Report
NIST IR 8485 DRAFT SUPPLEMENT**

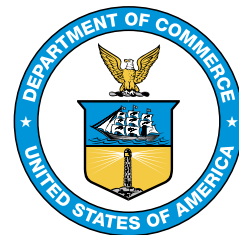
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Image Group

*Information Access Division
Information Technology Laboratory*

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April 2024



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Abstract

This report summarizes the results of the FATE Quality Vector assessment track, which tests face image quality algorithms' ability to detect specific defects such as non-frontal pose and background non-uniformity in the context of facial images. All algorithms submitted have some success at measuring various quality-related parameters.

Keywords

Face; defect; detection; image; quality; quality component; quality measure; specific.

EXECUTIVE SUMMARY

This report summarizes results from the Face Analysis Technology Evaluation (FATE) Quality Specific Image Defect Detection (SIDDD) activity. All algorithms submitted have some success at measuring various quality-related parameters. The measures that were implemented most frequently include total faces present, pitch, yaw, roll, eyes open, and inter-eye distance. As ISO/IEC 29794-5:2024 is finalized, we will continue to add, replace, and extend test cases and test datasets, to support development and to identify core capability. As this report is scrutinized by developers and end-users, comments and participation from other developers are welcomed.

RELEASE NOTES

2024-04-16: The FATE Quality SIDD track remains open. Developers should wait four months from their last (successful) submission to submit a new submission.

- ▷ We have added results for two new submissions: igd_003 and roc_007.
- ▷ We have reduced the range of the y-axis in the Pitch Set 1, Pitch Set 2, and Roll plots so that the violins are more clearly readable.

2024-04-05: Starting today, we are implementing a four-month waiting period; developers should wait four months from their last (successful) submission to submit a new submission.

2024-03-29: The FATE Quality SIDD track remains open. Developers should wait until one week following the release of the results of their last submission to submit a new submission.

- ▷ Due to a systematic offset in the determination of ground truth for Pitch Set 2, we have increased ground truth pitch values by 10 degrees; that is, each violin's x-coordinate has increased by 10 in Figure 7. Table 5 has been updated accordingly. The Frankfurt Horizon may have been used to determine pitch in the initial collection, causing the offset.

2024-03-08: The FATE Quality SIDD track remains open. Developers should wait until one week following the release of the results of their last submission to submit a new submission.

- ▷ We have added results for one new submission: mobbl_000.

2024-02-14: The FATE Quality SIDD track remains open. Developers should wait until one week following the release of the results of their last submission to submit a new submission.

- ▷ We have added results for two new submissions: roc_006 and viante_000.

2024-02-02: The FATE Quality SIDD track remains open. Developers should wait until one week following the release of the results of their last submission to submit a new submission.

- ▷ We have added results for one submission: igd_002.
- ▷ We have changed the EyeGlassesPresent violin plot to a confusion matrix to show detection and error rates based on a threshold.

2023-12-29: The FATE Quality SIDD track remains open. Developers should wait until one week following the release of the results of their last submission to submit a new submission.

- ▷ We have added results for two new submissions: datech_000 and vsoft_002.

2023-12-15: The FATE Quality SIDD track remains open. Developers should wait until one week following the release of a report to submit a new submission.

- ▷ We have added results for two new submissions: seamfix_002 and neurotechnology_004.
- ▷ The Unified Quality Score panel for digidata.001 was previously calculated based on an FNMR average from only two recognition algorithms; it has been updated to be based on an FNMR average from 15 recognition algorithms, consistent with the other panels.
- ▷ We have added a set for Inter-Eye Distance with non-zero yaw: Inter-Eye Distance Set 3.

2023-12-01: The FATE Quality SIDD track remains open. From this point forward, developers should wait until one week following the release of a report to submit a new submission.

- ▷ We have added results for two new submissions: secunet_003 and secunet_004.
- ▷ There are two images for Eyes Open for which we have corrected the ground truth values.
- ▷ We have added three measures: Eyes Open2, MouthOpen 2, and FaceOcclusion 2. As described in our API Concept Document, these modify the Eyes Open, Mouth Open, and Face Occlusion measures and are aligned with ISO/IEC:29794-5.

The original measures, Eyes Open, Mouth Open, and Face Occlusion should no longer be implemented, and will not be evaluated if they are implemented from this point forward.

2023-11-06: The FATE Quality SIDD track remains open.

- ▷ We have added results for three new submissions: Dermalog, IDEMIA, and SeamFix.
- ▷ For quality measures for which we report error with respect to ground truth, we are now reporting mean absolute error instead of median absolute error. The mean absolute error includes a penalty for failures to detect a face. The penalty is described in the caption of the plots when such failures occur.
- ▷ We have added two sets for manually estimated pitch and yaw: Pitch Set 3 and Yaw Set 3.

2023-10-13: The FATE Quality SIDD track remains open.

- ▷ We have added results for one new submission: Fraunhofer IGD.
- ▷ Yaw Set 2 previously contained three copies of each image at different sizes. We have fixed this issue, so the largest size of each image is now present, and others have been removed.

- ▷ The matrix showing performance for Total Faces Present has been updated so that when the estimated face count is not given, we report an estimated count of zero faces.
- ▷ We have updated the Face Occlusion plot with the count of instances when the algorithm did not return an estimate.

2023-09-19: The FATE Quality SIDD track remains open.

- ▷ This document is the first release of the Quality SIDD report. It contains results for seven submissions from five participants: Digidata, FRP, Secunet, Neurotechnology, and Rank One.

The procedure and format of submissions to the evaluation can be found in the API document [[PDF](#)].

Table of Contents

Executive Summary	ii
Release Notes	iii
1. Introduction	1
2. Test Sets	1
2.1. Development	1
2.2. Limitations	2
2.3. Test Set Sizes	2
3. Algorithms and Results	4
3.1. Algorithms	4
3.2. Quality Measures Supported	5
3.3. Timing	8
3.4. Total Faces Present	10
3.4.1. Images Used	10
3.4.2. Results for Total Faces Present	10
3.5. Yaw Angle	12
3.5.1. Images Used	12
3.5.2. Results for Yaw Angle	12
3.6. Pitch Angle	17
3.6.1. Images Used	17
3.6.2. Results for Pitch Angle	17
3.7. Roll Angle	22
3.7.1. Images Used	22
3.7.2. Results for Roll Angle	22
3.8. Eyes Open	24
3.8.1. Images Used	24
3.8.2. Results for Eyes Open	24
3.9. Eyes Open 2	26
3.9.1. Images Used	26
3.9.2. Results for Eyes Open 2	26
3.10. Inter-Eye Distance	28
3.10.1. Images Used	28

3.10.2. Results for Inter-Eye Distance	29
3.11. Mouth Open	34
3.11.1. Images Used	34
3.11.2. Results for Mouth Open	35
3.12. Mouth Open 2	37
3.12.1. Images Used	37
3.12.2. Results for Mouth Open 2	38
3.13. Background Uniformity	39
3.13.1. Images Used	39
3.13.2. Results for Background Uniformity	40
3.14. Resolution	41
3.14.1. Images Used	41
3.14.2. Effect of Gaussian Blur on IED Error	41
3.14.3. Results for Resolution	41
3.15. Underexposure	46
3.15.1. Images Used	46
3.15.2. Results for Underexposure	47
3.16. Overexposure	48
3.16.1. Images Used	48
3.16.2. Results for Overexposure	49
3.17. Eyeglasses Present	50
3.17.1. Images Used	50
3.17.2. Results for Eyeglasses Present	50
3.18. Sunglasses Present	52
3.18.1. Images Used	52
3.18.2. Results for Sunglasses Present	52
3.19. Compression Artifacts	53
3.19.1. Images Used	53
3.19.2. Results for Compression Artifacts	53
3.20. Face Occlusion	55
3.20.1. Images Used	55

3.20.2. Results for Face Occlusion	55
3.21. Face Occlusion 2	57
3.21.1. Images Used	57
3.21.2. Results for Face Occlusion 2	57
3.22. Motion Blur	59
3.22.1. Images Used	59
3.22.2. Results for Motion Blur	59
3.23. Distance from Eyes to Edges	61
3.23.1. Images Used	61
3.23.2. Results for Distance from Eyes to Edges	61
3.24. Unified Quality Score	64
3.24.1. Results for Unified Quality Score	64

List of Tables

Table 1. Set Sizes	3
Table 2. Quality SIDD Assessment Participants	4
Table 3. Quality Measures Supported	6
Table 4. Subject Yaw: Mean Absolute Error	13
Table 5. Subject Pitch: Mean Absolute Error	18
Table 6. Subject Roll: Mean Absolute Error	22
Table 7. Normalized Eye Aperture: Mean Absolute Error	24
Table 8. IED Mean Absolute Error	30
Table 9. Normalized Mouth Aperture: Mean Absolute Error	35
Table 10. Images in order of increasing background uniformity	39
Table 11. Resolution Illustration	41
Table 12. Underexposure Illustration	46
Table 13. Overexposure Illustration	48
Table 14. Compression Artifacts Illustration	53
Table 15. Face Occlusion Illustration	55
Table 16. Face Occlusion 2 Illustration	57
Table 17. Motion Blur Illustration	59

List of Figures

Fig. 1. Timing Performance	9
Fig. 2. Total Number of Faces	11
Fig. 3. Angle of Yaw Set 1	14
Fig. 4. Angle of Yaw Set 2	15
Fig. 5. Angle of Yaw Set 3	16

Fig. 6.	Angle of Pitch Set 1	19
Fig. 7.	Angle of Pitch Set 2	20
Fig. 8.	Angle of Pitch Set 3	21
Fig. 9.	Angle of Roll	23
Fig. 10.	Eyes Open Illustration	24
Fig. 11.	Mugshot Images: Eyes Open	25
Fig. 12.	Eyes Open 2 Illustration	26
Fig. 13.	Mugshot Images: Eyes Open 2	27
Fig. 14.	2D Inter-Eye Distance Illustration	28
Fig. 15.	3D Inter-Eye Distance Illustration	29
Fig. 16.	Inter-Eye Distance	31
Fig. 17.	Inter-Eye Distance	32
Fig. 18.	Error in Inter-Eye Distance with Yaw	33
Fig. 19.	Mouth Open Illustration	34
Fig. 20.	Mugshot Images: Mouth Open	36
Fig. 21.	Mouth Open 2 Illustration	37
Fig. 22.	Mugshot Images: Mouth Open 2	38
Fig. 23.	Mugshot Images: Background Uniformity	40
Fig. 25.	Inter-eye Distance Error Increases With Gaussian Blur	44
Fig. 26.	Synthetic Defect: Resolution	45
Fig. 27.	Synthetic Defect: Underexposure	47
Fig. 28.	Synthetic Defect: Overexposure	49
Fig. 29.	EyeGlassesPresent	51
Fig. 30.	SunGlassesPresent	52
Fig. 31.	Compression Artifacts	54
Fig. 32.	Face Occlusion	56
Fig. 33.	Face Occlusion 2	58
Fig. 34.	Motion Blur	60
Fig. 35.	Distance From Eyes To Edges Illustration	61
Fig. 36.	Pixels From Eye to Left Edge	62
Fig. 37.	Pixels From Eye to Right Edge	62
Fig. 38.	Pixels From Eyes to Bottom	63
Fig. 39.	Pixels From Eyes to Top	63
Fig. 41.	Unified Quality Score Performance for Several Initial FNMR Values	66

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Other Relevant Reports

Results from the Face Recognition Technology Evaluation (FRTE) and Face Analysis Technology Evaluation (FATE) activities appear in the series of NIST Interagency Reports tabulated below. From 1999 to July 2023, FRTE and FATE were collectively known as FRVT.

DATE	PROG.	NISTIR	TITLE
2014-03-20	FATE	7995	Performance of Automated Age Estimation Algorithms
2015-04-20	FATE	8052	Performance of Automated Gender Classification Algorithms
2014-05-21	FRTE	8009	Performance of Face Identification Algorithms
2017-03-07	FRTE	8173	FIVE - Face In Video Evaluation: Face Recognition of Non-Cooperative Subjects
2017-11-23	FRTE	8197	FRPC - The 2017 IARPA Face Recognition Prize Challenge
2020-01-03	FRTE	Draft	Part 1: Verification
2019-09-11	FRTE	8271	Part 2: Identification
2019-12-11	FRTE	8280	Part 3: Demographic Effects
2020-03-04	FATE	8292	Part 4: MORPH - Performance of Automated Face Morph Detection
2020-03-06	FATE	Draft	Part 5: Face Image Quality Assessment
2020-07-24	FRTE	8311	Part 6A: Face Recognition Accuracy with Face Masks using Pre-COVID-19 Algorithms
2022-01-20	FRTE	8331	Part 6B: Face Recognition Accuracy with Face Masks using Post-COVID-19 Algorithms
2022-07-13	FRTE	8381	Part 7: Identification for Paperless Travel and Immigration
2022-09-30	FRTE	PDF	Part 8: Summarizing Demographic Differentials
2022-09-30	FRTE	8439	Part 9A: Face Recognition Verification Accuracy on Distinguishing Twins
2023-09-20	FATE	8491	Part 10: Performance of Passive Software-based Presentation Attack Detection (PAD) Algorithms
2023-09-20	FATE	8485	Part 11: Face Image Quality Vector Assessment: Specific Image Defect Detection

Details appear on pages linked from <https://www.nist.gov/programs-projects/face-projects>.

1. Introduction

Consider the procedure of taking a passport photo: whether for renewal or obtaining a visa, there are formal standards that the capture subject and photographer must follow in order to take an acceptable photo. These standards vary in the required photo size, but commonly require a frontal viewpoint, open eyes, a neutral expression, a uniform background, and other criteria to be fulfilled; for a detailed discussion of these criteria, see Annex D1 of [ISO/IEC 39794-5:2019](#). These standards and the practices needed to conform to them are intended to support highly accurate face recognition by ensuring that the captured photo can serve as a high quality reference photo in a machine readable travel document (e.g. passport) or in a reference database (e.g. the IDENT system in the US, or the EU-VIS BMS system in Europe).

This Face Analysis Technology Evaluation (FATE) track, Specific Image Defect Detection (SIDD), is being conducted to support quality assessment in general, and to support assessment of quality component algorithms that implement the quality checks of ISO/IEC 29794-5:2024 (under development). That standard enumerates checks on face photos that derive from [ISO/IEC 19794-5:2011](#), which established photographic and subject appearance requirements for enrollment images in the European Entry-Exit-System (according to [EU-EES implementing decision 2019/329](#)), and [ISO/IEC 39794-5:2019](#), which refined and extended photograph specification and will be used for e-Passports from 2030 onwards.

The existing FATE [Quality Summarization Track](#) is an ongoing track that examines the relation between quality score and false non-match rates in order to gauge how well a quality component algorithm can predict false negative errors. However, it does not differentiate between different factors (i.e. quality components) that affect quality. In the SIDD track, we delve deeper into a nuanced discussion of quality measures.

The procedure and format of submissions to our evaluation are described in the Quality SIDD Assessment [API document](#).

2. Test Sets

2.1. Development

The Quality SIDD assessment proceeds by passing photographs to algorithms using a NIST-defined C++ API. The test sets consist of images sequestered at NIST, i.e. developers do not have access to the images. NIST has curated sets specifically to evaluate the performance of algorithms measuring the quantities given in Table 3. For example, there are various sets of frontal and non-frontal images to evaluate pose estimation accuracy; the images in these sets have known pitch and yaw angles.

We formulate ground truth for test sets using three approaches:

- **Camera placement:** At the time of capture, a camera is placed at a specific angle to the subject.
- **Manual labeling:** We determine ground truth by human inspection, by measuring the desired quantity using software such as GIMP.
- **Synthetic degradation:** We generate images with different degrees of a defect (blur, overexposure and underexposure) by applying varying amounts of a defect to a natural image.

This section contains results from all algorithms submitted from the inception of the Quality SIDD evaluation in July 2022.

2.2. Limitations

For several measures, such as inter-eye distance and mouth aperture, we use ground truth that is determined by human inspection. This style of testing, in which ground truth is a continuous variable with some measurement error, means that the software can never be perfect. This is in contrast to a recognition test, for example, where labels are discrete and, ideally, error-free.

2.3. Test Set Sizes

Table 1 lists the number of images in each test set for the quality measures that were implemented so far.

Table 1. Set sizes. This table presents the quality measures in the SIDD track and the number of images in each test set.

Dataset	Number of Images
TotalFacesPresent	92
SubjectPosePitch-1	6291
SubjectPosePitch-2	7145
SubjectPosePitch-3	288
SubjectPoseYaw-1	6267
SubjectPoseYaw-2	11338
SubjectPoseYaw-3	288
SubjectPoseRoll	12000
EyesOpen	107
EyesOpen2	107
InterEyeDistance-1	40
InterEyeDistance-2	39
InterEyeDistance-3	1800
MouthOpen	145
MouthOpen2	145
BackgroundUniformity	229
Resolution	8000
Underexposure	250
Overexposure	250
EyeGlassesPresent	279
SunGlassesPresent	40
CompressionArtifacts	500
FaceOcclusion	30
FaceOcclusion2	30
MotionBlur	6000
PixelsFromEyeToLeftEdge	40
PixelsFromEyeToRightEdge	40
PixelsFromEyesToTop	40
PixelsFromEyesToBottom	40

3. Algorithms and Results

3.1. Algorithms

Table 2 lists the participants who submitted algorithms to the Quality SIDD Assessment.

Table 2. Quality SIDD Assessment Participants

Participant Name	Short Name	Sequence Number	Submission Date
Digidata	digidata	001	2022.09.29
FRP LLC	frpkauai	000	2022.10.28
Secunet Security Networks AG (part of OFIQ)	secunet	001	2023.02.16
Secunet Security Networks AG (part of OFIQ)	secunet	002	2023.04.21
Neurotechnology	neurotechnology	002	2023.07.10
Rank One Computing	rankone	005	2023.07.14
Neurotechnology	neurotechnology	003	2023.08.10
Fraunhofer IGD	igd	001	2023.09.18
Idemia	idemia	002	2023.10.16
Dermalog	dermalog	002	2023.10.19
Seamfix Limited	seamfix	001	2023.10.23
Secunet Security Networks AG (part of OFIQ)	secunet	004	2023.11.17
Secunet Security Networks AG (part of OFIQ)	secunet	003	2023.11.24
Seamfix Limited	seamfix	002	2023.11.24
Neurotechnology	neurotechnology	004	2023.12.06
Dactionable Technologies	datech	000	2023.12.08
Vsoft	vsoft	002	2023.12.11
Fraunhofer IGD	igd	002	2024.01.22
ROC	roc	006	2024.02.05
Viante.AI	viante	000	2024.02.06
Mobbeel Solutions	mobbl	000	2024.02.22
Fraunhofer IGD	igd	003	2024.03.28
ROC	roc	007	2024.04.05

3.2. Quality Measures Supported

Table 3 lists the quality measures defined in our API and the algorithms that implement them. The first row indicates whether the quality measure must be checked for an image to be used as a reference image in a machine-readable travel document (MRTD) such as a passport, which is Use Case 1 (UC1) as listed in ISO/IEC 29794-5:2024.

Table 3. Quality Measures Supported. This table presents the participating algorithm name and which SIDD quality measures were implemented. A 'Y' (for 'Yes') indicates that the quality measure is implemented; a blank space indicates that it is not implemented. The first row indicates which quality measures are required to be checked for use as a reference photo in a machine-readable travel document (MRTD) according to ISO/IEC 29794-5:2024.

Algorithm	TotalFacesPresent	SubjectPosePitch	SubjectPoseYaw	SubjectPoseRoll	EyesOpen	EyesOpen2	InterEyeDistance	MouthOpen	MouthOpen2	BackgroundUniformity	Resolution	Underexposure	Overexposure	PixelsFromEyeToLeftEdge	PixelsFromEyeToRightEdge	PixelsFromEyesToTop	PixelsFromEyesToBottom	EyeGlassesPresent	SunGlassesPresent	CompressionArtifacts	FaceOcclusion	FaceOcclusion2	MotionBlur	UnifiedQualityScore
Required for MRTD	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y						Y	Y
digidata-001	Y	Y	Y	Y	Y		Y	Y			Y	Y	Y											Y
frpkauai-000	Y	Y	Y	Y	Y		Y			Y	Y													
secunet-001	Y	Y	Y	Y	Y		Y	Y		Y		Y	Y											
secunet-002	Y	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y											Y
neurotechnology-002	Y	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y
rankone-005	Y	Y	Y	Y	Y		Y	Y			Y			Y	Y	Y	Y	Y	Y	Y	Y		Y	Y
neurotechnology-003	Y	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y
igd-001	Y	Y	Y	Y			Y				Y	Y	Y	Y	Y	Y	Y							
idemia-002	Y	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y
dermalog-002	Y	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y					Y
seamfix-001	Y	Y	Y	Y				Y		Y	Y	Y	Y					Y	Y					
secunet-004	Y	Y	Y	Y			Y			Y	Y									Y		Y		Y
secunet-003	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y			Y	Y	Y	Y	Y
seamfix-002	Y	Y	Y	Y						Y	Y	Y	Y					Y	Y				Y	Y
neurotechnology-004	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y
datech-000	Y																							Y
vsoft-002																								Y
igd-002	Y	Y	Y	Y		Y	Y		Y		Y	Y	Y	Y	Y	Y	Y							
roc-006	Y	Y	Y	Y		Y	Y				Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y

Table 3. Quality Measures Supported. This table presents the participating algorithm name and which SIDD quality measures were implemented. A 'Y' (for 'Yes') indicates that the quality measure is implemented; a blank space indicates that it is not implemented. The first row indicates which quality measures are required to be checked for use as a reference photo in a machine-readable travel document (MRTD) according to ISO/IEC 29794-5:2024. *(continued)*

Algorithm	TotalFacesPresent	SubjectPosePitch	SubjectPoseYaw	SubjectPoseRoll	EyesOpen	EyesOpen2	InterEyeDistance	MouthOpen	MouthOpen2	BackgroundUniformity	Resolution	Underexposure	Overexposure	PixelsFromEyeToLeftEdge	PixelsFromEyeToRightEdge	PixelsFromEyesToTop	PixelsFromEyesToBottom	EyeGlassesPresent	SunGlassesPresent	CompressionArtifacts	FaceOcclusion	FaceOcclusion2	MotionBlur	UnifiedQualityScore
viante-000	Y	Y	Y	Y		Y	Y		Y		Y	Y	Y	Y	Y	Y	Y	Y	Y			Y	Y	Y
mobbl-000	Y	Y	Y	Y		Y	Y		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y
igd-003	Y	Y	Y	Y		Y	Y		Y		Y	Y	Y	Y	Y	Y	Y		Y			Y		
roc-007	Y	Y	Y	Y		Y	Y				Y	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y

3.3. Timing

The duration of execution of quality algorithm (QA) software is important in those applications where fast quantification is needed to support usability by providing usable feedback to a capture subject. It may be important also, for example, in running QA software over large legacy collections. This section gives duration of the various implementations running on a common hardware platform.

Figure 1 shows the timing performance for the participants who submitted algorithms to the Quality SIDD Assessment.

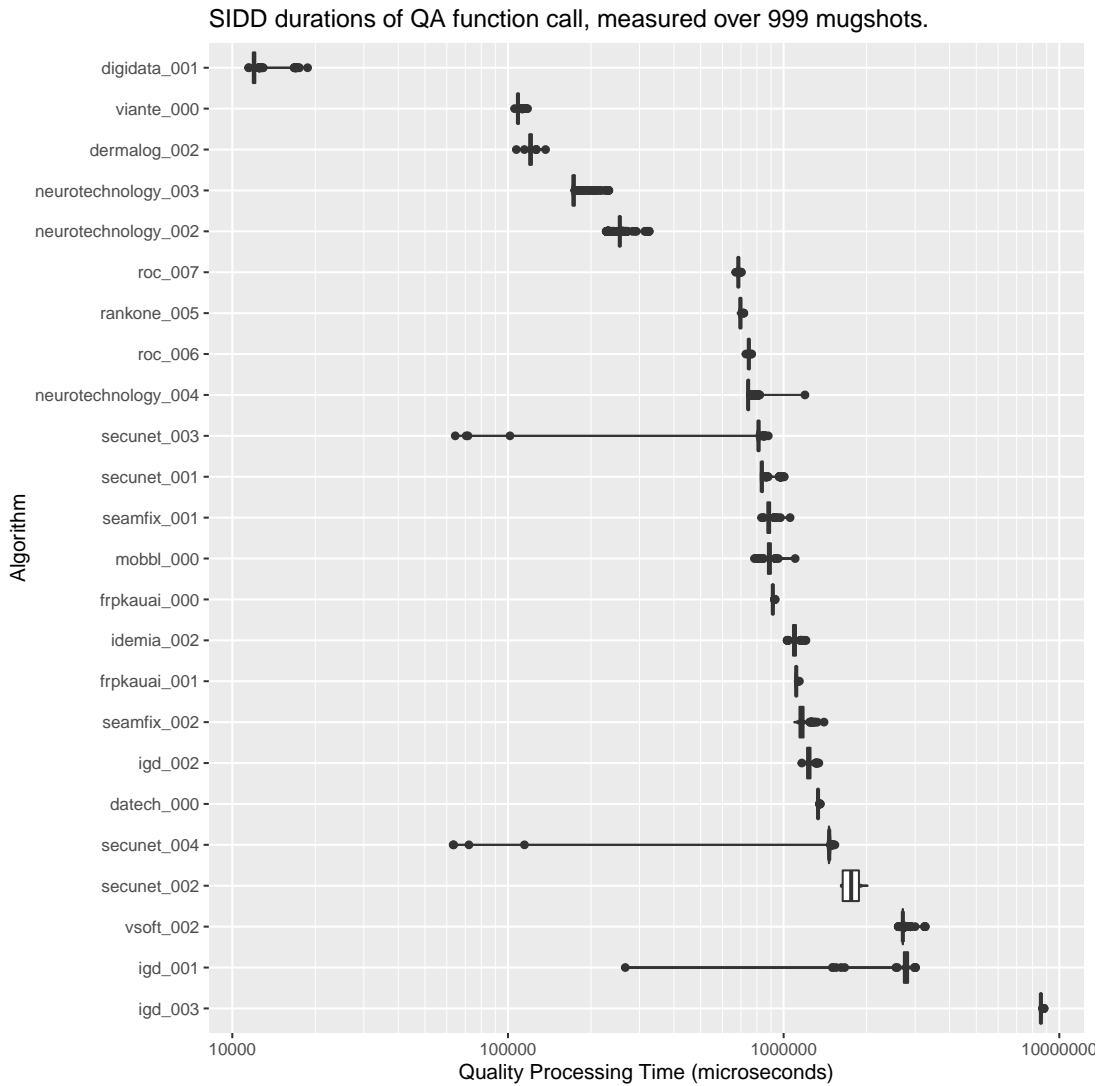


Fig. 1. Distribution of time required for the quality algorithm (QA) function call, measured over 999 mugshots. The implementations vary, in part, because they are computing different quality components – see Table 3. Durations are measured on a fixed Intel Xeon Gold 6140 CPU running at 2.30 GHz. Durations are measured by wrapping the function call in a high resolution timer.

3.4. Total Faces Present

3.4.1. Images Used

The images in the Total Faces Present dataset are captured in a border-crossing setting with a variety of poses and some background non-uniformity. The input images generally have one primary face that is larger than the others. We count faces manually, where a face is counted if its inter-eye distance is estimated to be larger than 0.02 times the width of the image.

3.4.2. Results for Total Faces Present

Figure 2 summarizes the performance of all algorithms that implemented the Total Faces Present measure. Note that there are more missed detections (below the diagonal) than false detections (above the diagonal). Missed detection rate is the number of missed faces divided by the total number of faces; false detection rate is the average number of wrong detections per image. For both false detection rate and missed detection rate, lower values are better.

SIDD Component: TotalFacesPresent: Estimated vs. true number of faces in image



Fig. 2. Estimated number of faces vs. known number of faces. Perfect performance corresponds to zero on off-diagonal entries and 1 on each of the diagonal entries. Each column is normalized by the sum along that column, so that the numbers give estimates of the rate at which the software gives a false detection (above the diagonal), missed detection (below the diagonal), and correct detection (on the diagonal). Missed detections can occur because algorithms are configured to only detect faces larger than a certain size. The value at (x,y) is the proportion of images with known number of faces x and detected number of faces y . Missed detection rate is the number of missed faces divided by the total number of faces; false detection rate is the average number of wrong detections per image.

3.5. Yaw Angle

3.5.1. Images Used

The images for the Yaw quality measure are from three sets of sequestered photos. The images in these sets have a well-illuminated setting with a uniform background.

1. For the first set, at the time of capture, a camera is placed to the right or left of the subject at varying angles, with the subject remaining frontal and stationary. Yaw is recorded at the time of collection.
2. For the second set, at the time of capture, the subject turns the head to look at a target to the left or right. Yaw is recorded at the time of collection.
3. For the third set, a camera is placed to the right or left of the subject at varying angles; the subject remains stationary and frontal. Ground truth yaw values are determined by rotating a computer-generated model of a head to match the subject's pose, and taking the corresponding yaw reading.

Camera placement to the subject's right corresponds to yaw being positive. Camera placement to the subject's left corresponds to yaw being negative. This sign convention is consistent with the ISO/IEC 39794-5:2019 standard.

3.5.2. Results for Yaw Angle

Table 4, Figure 3, Figure 4, and Figure 5 summarize algorithm performance. For images for which the algorithm does not detect a face, the error is 45 degrees. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

Table 4. SIDD PoseYaw Mean Absolute Error.

Algorithm	Yaw Set 1	Yaw Set 2	Yaw Set 3
viante_000	6.3	11.3	4.5
roc_006	6.7	10.8	5.5
roc_007	6.7	10.8	5.5
frpkauai_000	7.6	11.8	3.7
dermalog_002	7.8	13.2	5.8
idemia_002	8.8	12.5	2.9
neurotechnology_003	9.5	12.6	3.6
neurotechnology_002	9.6	12.4	3.6
digidata_001	11.3	20.3	5.1
secunet_004	11.4	11.3	4.0
secunet_002	11.6	14.6	4.2
rankone_005	11.8	12.1	5.3
secunet_003	13.8	12.4	3.6
mobbl_000	18.2	12.3	4.2
neurotechnology_004	19.6	14.1	3.2
seamfix_001	23.4	43.7	13.0
seamfix_002	23.4	43.7	13.0
igd_001	26.8	27.0	9.7
secunet_001	41.2	14.7	4.2
igd_003	47.8	37.1	12.3
igd_002	54.7	39.6	16.8

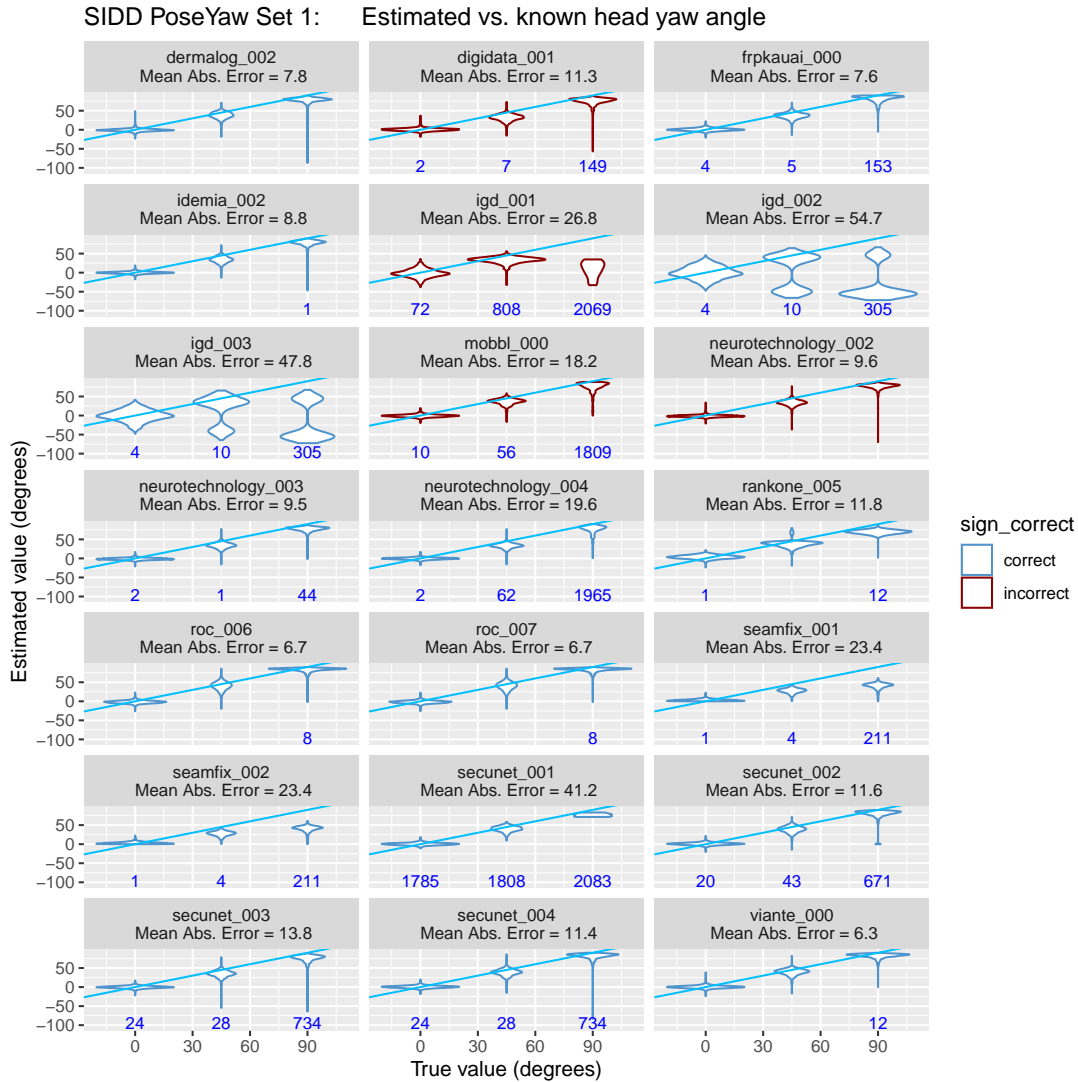


Fig. 3. Estimated vs. known values of yaw angle. For Yaw Set 1, ground truth yaw values are determined by the placement of the camera at the time of capture; the subject remains stationary and frontal. The blue line ($y = x$) represents perfect performance. The plot shows violins at true yaw values with the tails extending to the minimum and maximum estimated values. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 45 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate the scores in the next submission.

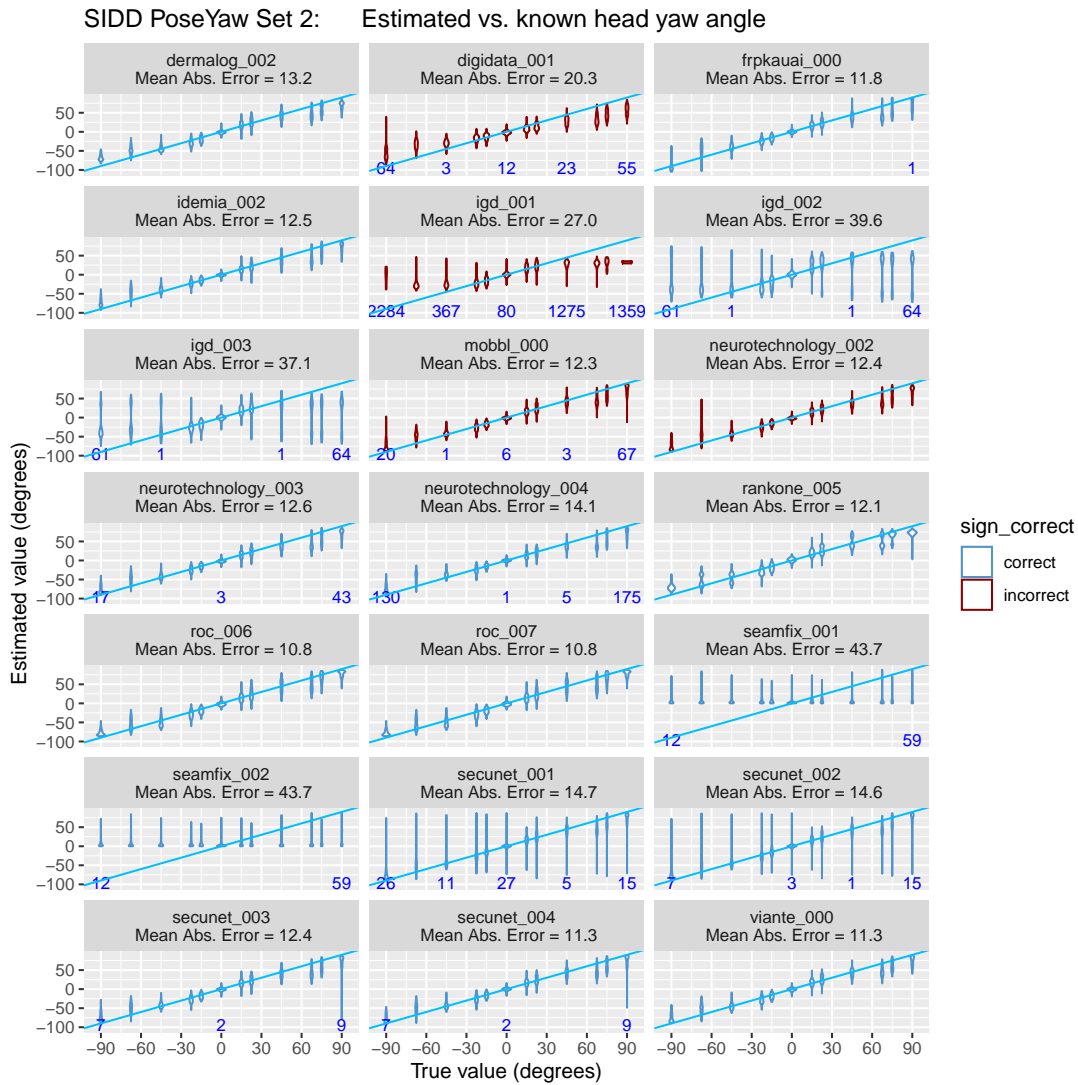


Fig. 4. Estimated vs. known values of yaw angle. For Yaw Set 2, the subject turns the head to look at targets placed to the right or left. The blue line ($y = x$) represents perfect performance. The plot shows violins at true yaw values with the tails extending to the minimum and maximum estimated values. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 45 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate the scores in the next submission.

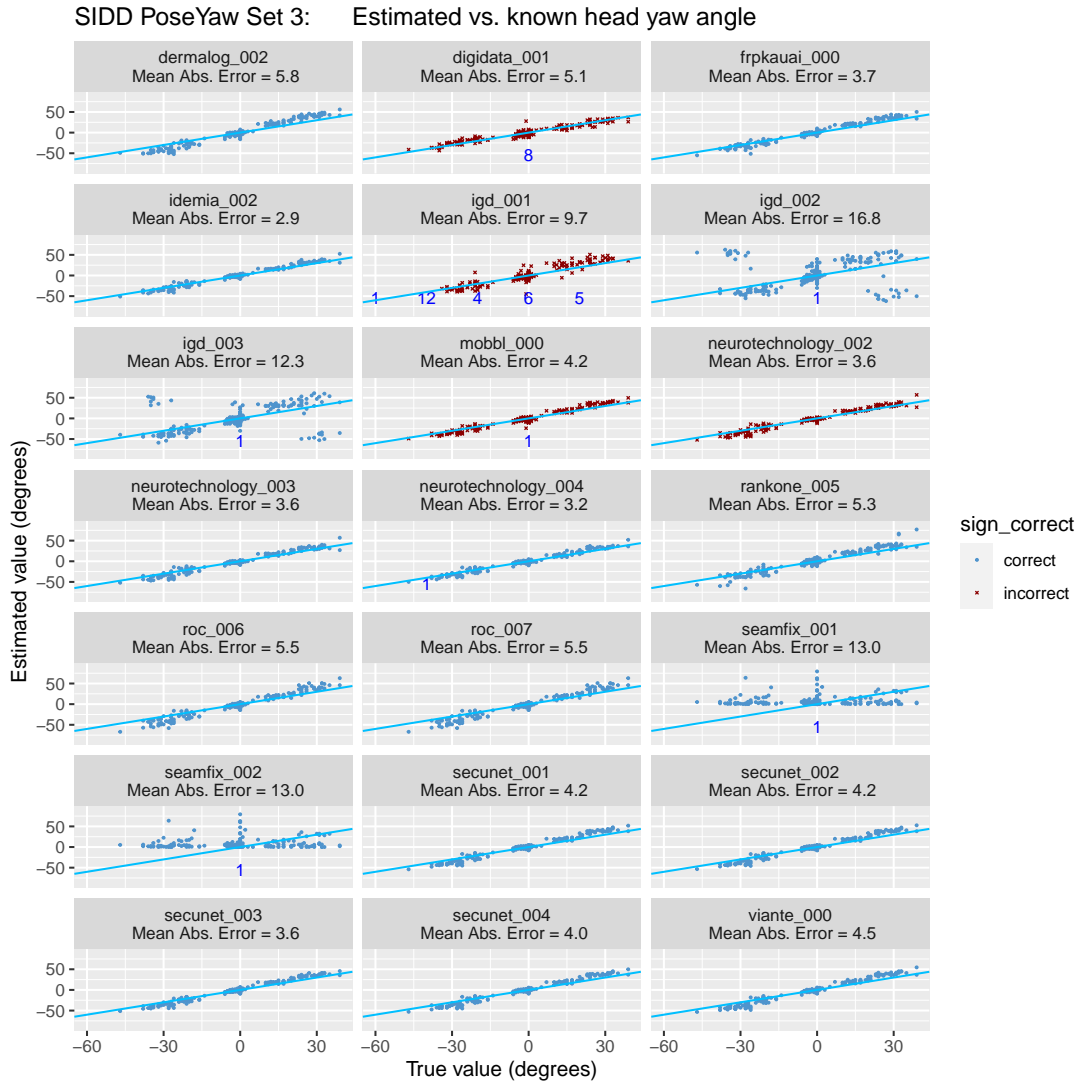


Fig. 5. Estimated vs. known values of yaw angle. For Yaw Set 3, a camera is placed to the right or left of the subject at varying angles; the subject remains stationary and frontal. Ground truth yaw values are determined by rotating a computer-generated model of a head to match the subject’s pose, and taking the corresponding yaw reading. The blue line ($y = x$) represents perfect performance. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 45 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate the scores in the next submission.

3.6. Pitch Angle

3.6.1. Images Used

The images for the Pitch quality measure are from three sets of sequestered photos.

1. In Set 1, the subject generally has a neutral position and is standing against a mostly uniform background, with some shadows behind the subject. At the time of capture, a camera is placed at varying heights; the subject is asked to be frontal. Pitch is recorded at the time of collection.
2. In Set 2, the subject is seated and is against a uniform background. At the time of capture, a camera is placed at varying heights; the subject is asked to be frontal. Pitch is recorded at the time of collection.
3. In Set 3, the subject raises or lowers the head to look at targets at varying heights. Ground truth pitch values are determined by rotating a computer-generated model of a head to match the subject's pose, and taking the corresponding pitch reading.

Camera placement above the subject, with the top of the head being more exposed, corresponds to pitch being positive, and placement below the subject, with the chin being more exposed, corresponds to pitch being negative. This sign convention is consistent with the ISO/IEC 39794-5:2019 standard.

3.6.2. Results for Pitch Angle

Table 5, Figure 6, Figure 7, and Figure 8 summarize the performance of the algorithms in our evaluation when estimating pitch angle. For images for which the algorithm does not detect a face, the error is 30 degrees. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

Note that the definition of zero-pitch is not as well-defined as zero-roll and zero-yaw.

Table 5. SIDD PosePitch Mean Absolute Error.

Algorithm	Pitch Set 1	Pitch Set 2	Pitch Set 3
secunet_004	6.6	14.5	5.3
secunet_002	6.6	13.0	4.9
neurotechnology_004	6.7	5.8	5.1
viant_000	7.0	7.5	4.7
neurotechnology_003	7.1	5.2	4.8
dermalog_002	7.3	7.0	5.1
mobbl_000	7.4	8.6	5.4
neurotechnology_002	7.5	5.2	5.0
secunet_003	7.9	10.6	4.8
digidata_001	8.0	7.4	5.6
seamfix_001	8.7	8.6	14.2
seamfix_002	8.7	8.6	14.2
idemia_002	10.2	9.7	4.8
roc_006	10.6	13.1	9.5
roc_007	10.6	13.1	9.5
frpkauai_000	12.7	8.8	5.5
igd_001	13.2	20.0	10.2
rankone_005	14.4	11.9	12.2
igd_002	15.0	12.1	11.4
igd_003	15.4	13.8	8.0
secunet_001	28.5	13.1	4.9

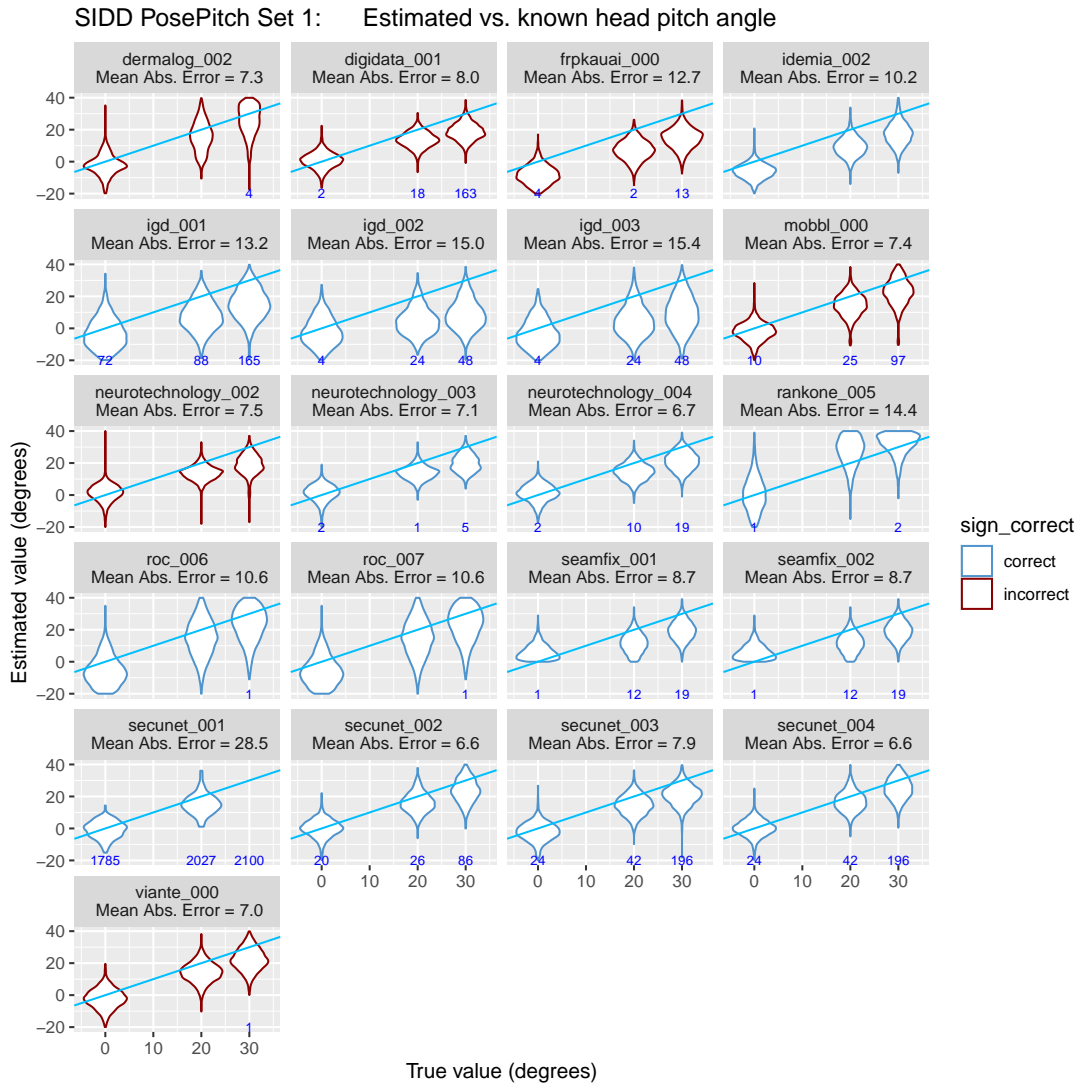


Fig. 6. Estimated vs. known values of pitch angle. For Pitch Set 1, ground truth pitch values are determined by the placement of the camera at the time of capture; the subject remains stationary and frontal. The blue line ($y = x$) represents perfect performance. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 30 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate the scores in the next submission.

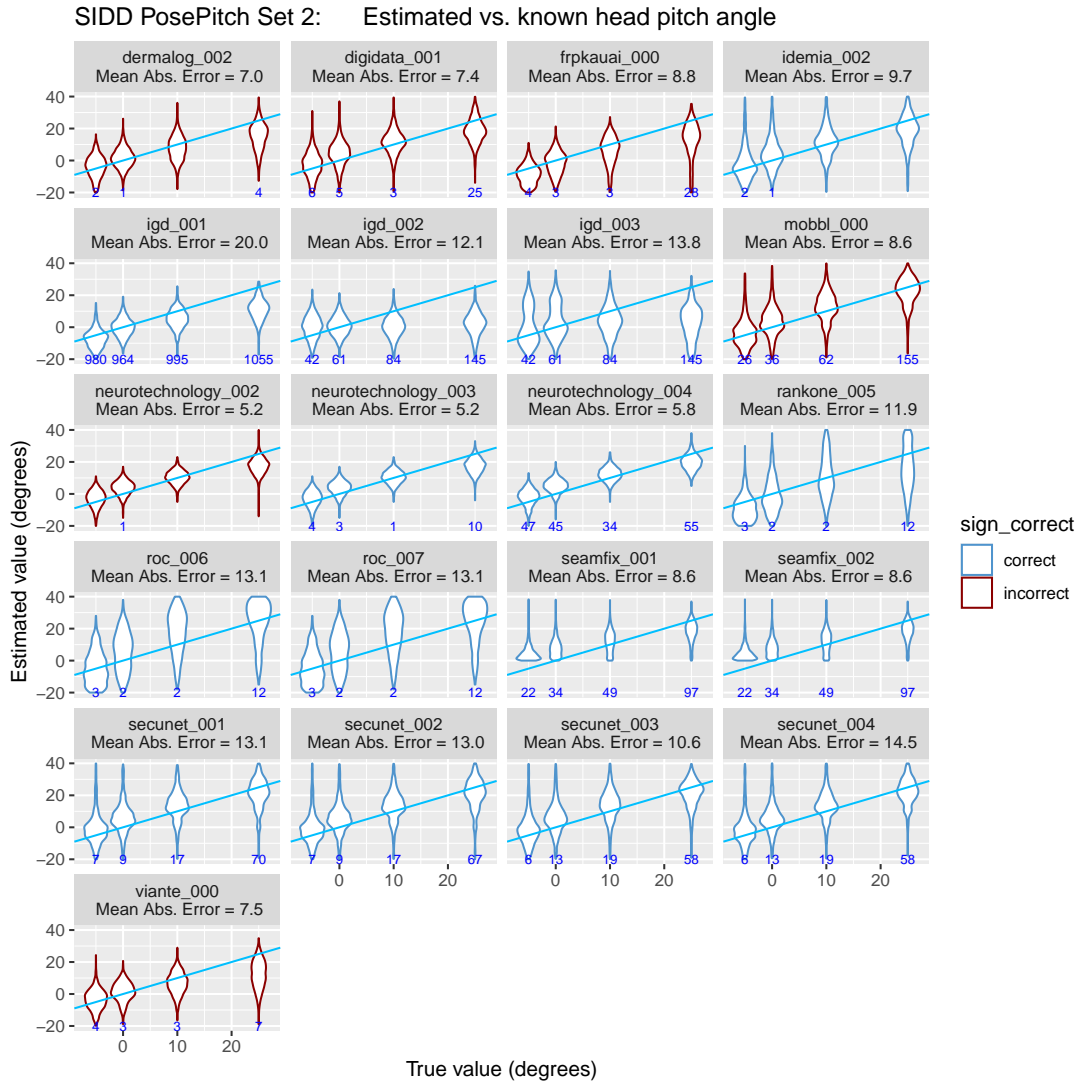


Fig. 7. Estimated vs. known values of pitch angle. For Pitch Set 2, ground truth pitch values are determined by the placement of the camera at the time of capture; the subject remains stationary and frontal. The blue line ($y = x$) represents perfect performance. The plot shows violins at true pitch values with tails extending to the minimum and maximum estimated values. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 30 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate the scores in the next submission.

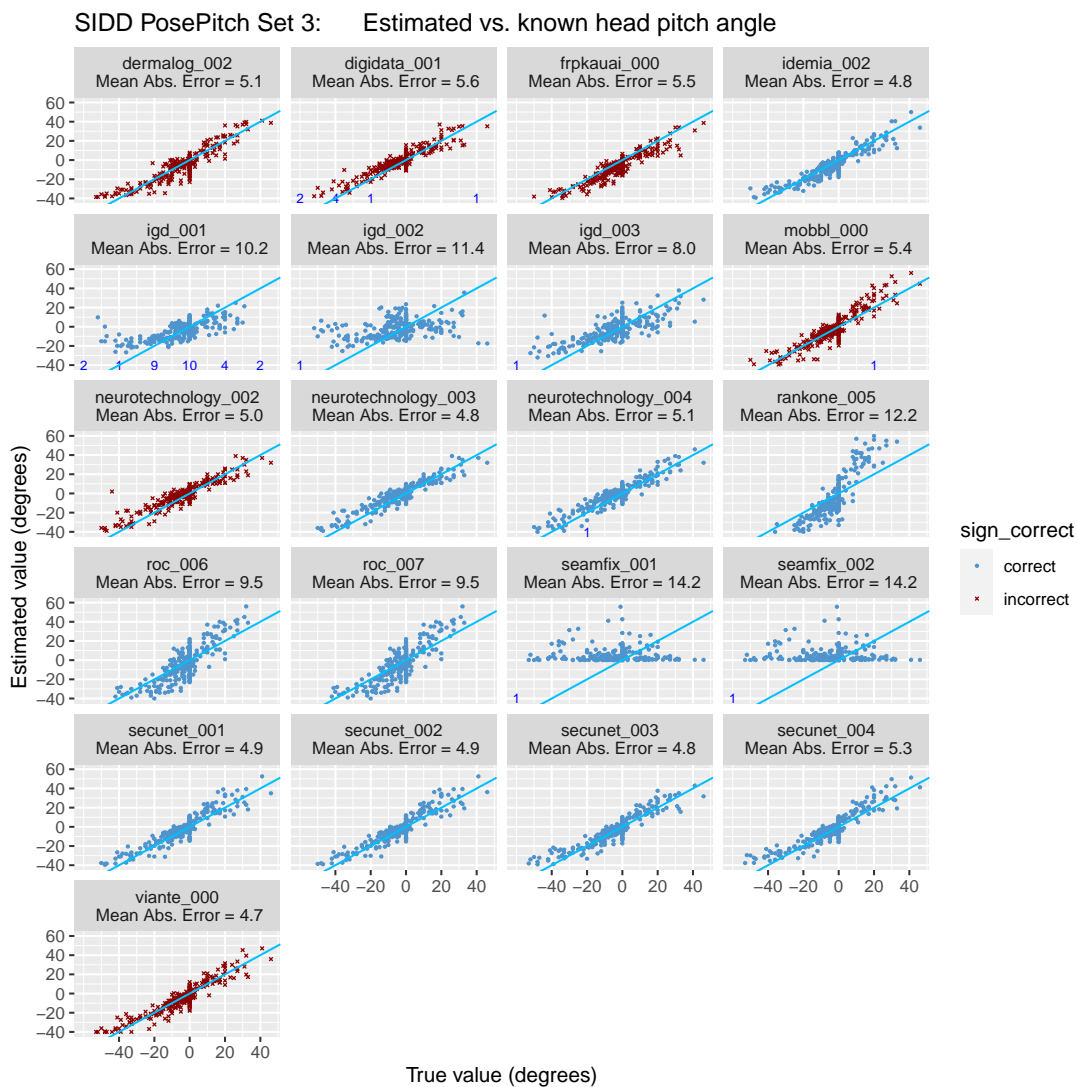


Fig. 8. Estimated vs. known values of pitch angle. For Pitch Set 3, the subject raises or lowers the head to look at targets at varying heights. Ground truth pitch values are determined by rotating a computer-generated model of a head to match the subject’s pose, and taking the corresponding pitch reading. The blue line ($y = x$) represents perfect performance. The plot shows violins at true pitch values with the tails extending to the minimum and maximum estimated values. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 30 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate the scores in the next submission.

3.7. Roll Angle

3.7.1. Images Used

The images in the Roll dataset are mugshots that are rotated by a roll angle ranging from -30 to 30 degrees. In particular, we do not include images with a roll angle of 90 degrees. Rotation towards the subject’s right shoulder corresponds to a positive roll angle. Rotation towards the subject’s left shoulder corresponds to a negative roll angle. This sign convention is consistent with the ISO/IEC 39794-5:2019 standard.

3.7.2. Results for Roll Angle

Table 6 and Figure 9 summarize the performance of the algorithms in our evaluation when estimating roll angle. For images for which the algorithm did not detect a face, the error is 45 degrees. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

Table 6. SIDD PoseRoll Mean Absolute Error

Algorithm	MAE (in degrees)
neurotechnology_004	0.9
idemia_002	1.2
viant_000	1.3
secunet_003	1.3
roc_006	1.4
roc_007	1.4
secunet_004	1.4
frpkauai_000	1.5
rankone_005	1.5
dermalog_002	1.7
neurotechnology_003	1.8
secunet_002	1.8
neurotechnology_002	1.8
secunet_001	1.8
mobbl_000	2.1
digidata_001	2.2
igd_002	2.6
igd_003	3.9
seamfix_001	8.2
seamfix_002	8.2
igd_001	9.9

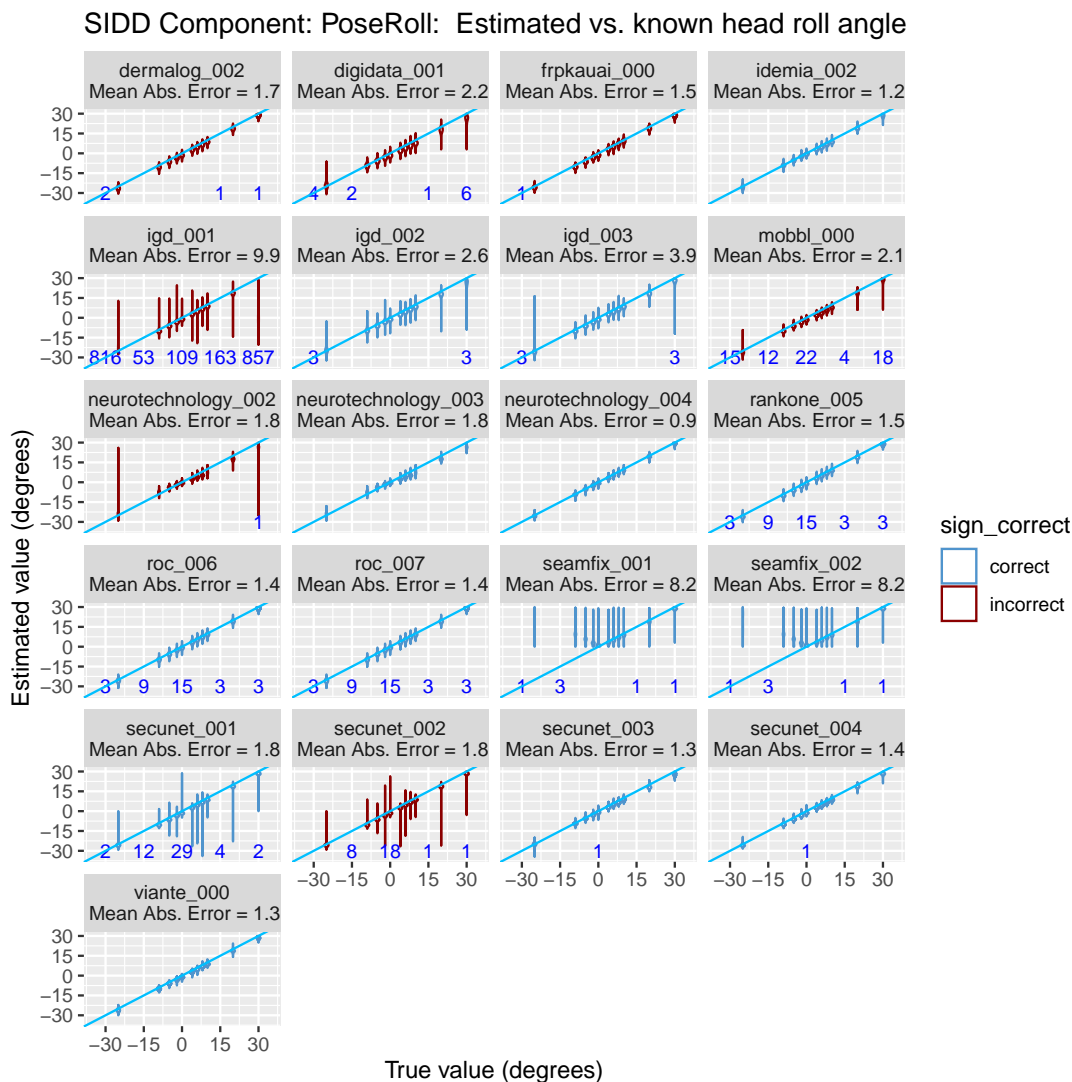


Fig. 9. Estimated vs. known values of roll angle. Ground truth roll values were determined by rotating mugshot images by a known angle. The blue line ($y = x$) represents perfect performance. The plot shows violins at true roll values with the tails extending to the minimum and maximum estimated values. The small blue numbers represent the count of images for which the software did not detect a face; for such images, the error is set to 45 degrees. The dark red color-coding indicates that the developer uses the opposite sign convention, and should negate their scores in the next submission.

3.8. Eyes Open

3.8.1. Images Used

The images for the Eyes Open test are mugshot images. We calculate the EyesOpen measure by comparing the left and right maximum apertures of the eyes as shown in Fig. 10, taking the minimum of the two values, and dividing the result by the inter-eye distance. This procedure correctly assigns a ground truth value of zero for eyes that are closed.

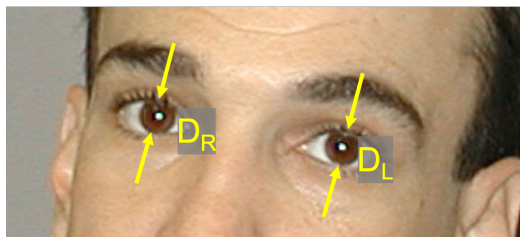


Fig. 10. The EyesOpen measure is computed by comparing the left and right maximum apertures of the eyes, taking the minimum of the two values, and dividing the result by inter-eye distance. Image from NIST Special Database 32, MEDS.

3.8.2. Results for Eyes Open

Table 7 and Figure 11 summarize algorithm performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

Table 7. SIDD EyesOpen Mean Absolute Error.

Algorithm	MAE (dimensionless)
secunet_003	0.02
idemia_002	0.03
neurotechnology_002	0.03
neurotechnology_003	0.03
secunet_002	0.03
secunet_001	0.03
digidata_001	0.03
rankone_005	0.15
dermalog_002	0.21
frpkauai_000	0.74

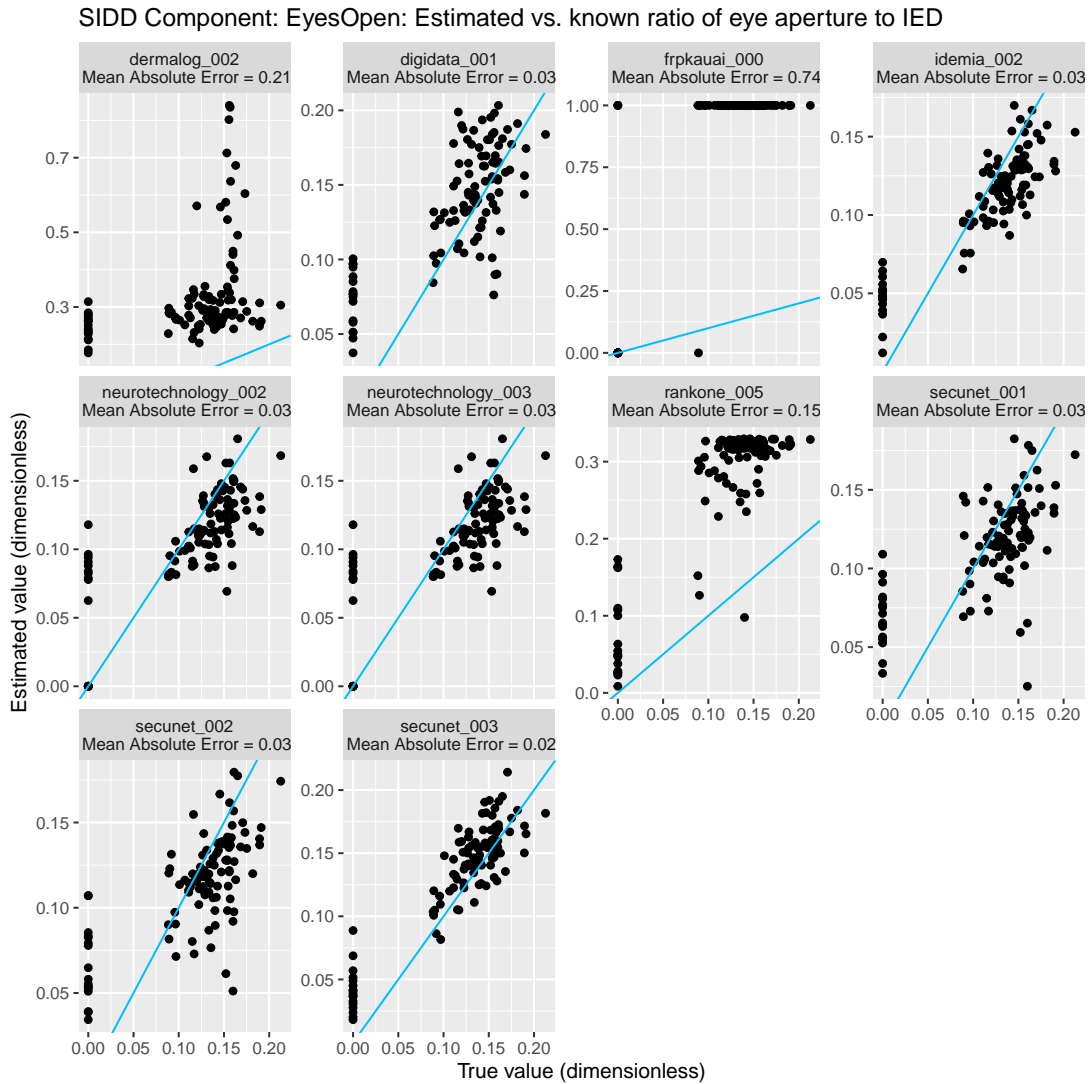


Fig. 11. Estimated vs. known values of the ratio of eye aperture to inter-eye distance. Ground truth preparation is discussed in Section 3.8.1. The blue line ($y = x$) represents perfect performance. The vertical line of dots at true value zero corresponds to closed eyes. Note that the plots have different y-axis ranges.

3.9. Eyes Open 2

3.9.1. Images Used

The images for the Eyes Open 2 measure are mugshot images. We calculate the EyesOpen2 measure by comparing the left and right maximum apertures of the eyes as shown in Fig. 12, taking the minimum of the two values, and dividing the result by the distance from the chin to the midpoint of the eye-centers. This procedure assigns a ground truth value of zero for eyes that are closed and is consistent with the ISO/IEC 29794-5 standard.



Fig. 12. The EyesOpen2 measure is computed by comparing the left and right maximum apertures of the eyes, taking the minimum of the two values, and dividing the result by the T-metric, the distance from the chin to the midpoint of the eye-centers. The eye apertures and the T-metric are computed perpendicular to the distance between the eyes. Image from NIST Special Database 32, MEDS.

3.9.2. Results for Eyes Open 2

Figure 13 summarizes algorithm performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

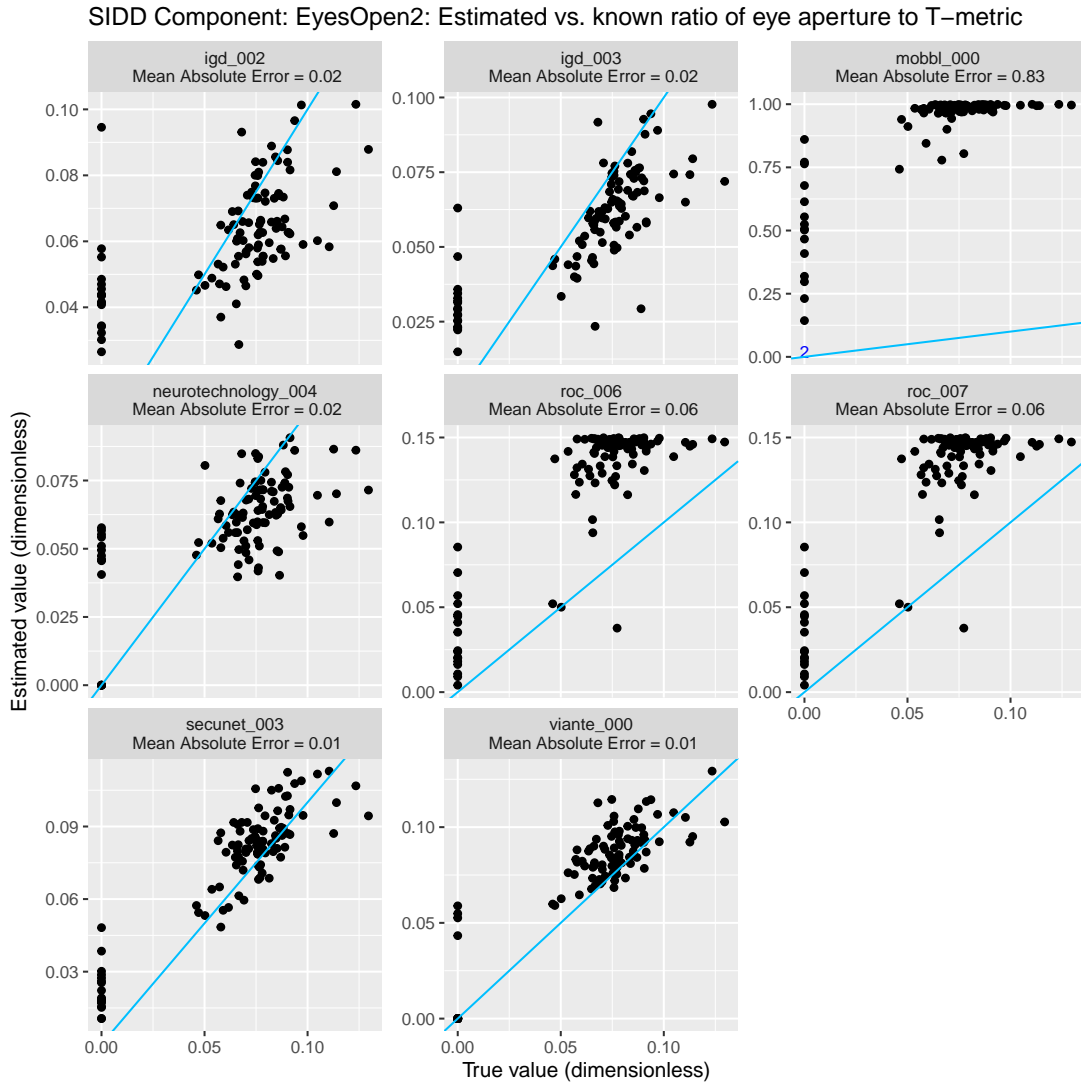


Fig. 13. Estimated vs. known values of the ratio of eye aperture to the distance T between the chin and midpoint of the eye-centers. Ground truth preparation is discussed in Section 3.9.1. The blue line ($y = x$) represents perfect performance. The vertical line of dots at true value zero corresponds to closed eyes. The small blue numbers along the x-axis represent instances when the algorithm did not detect a face; for such images, the error was set to 0.1.

3.10. Inter-Eye Distance

3.10.1. Images Used

The images for the Inter-Eye Distance test are from three sets: two sets of frontal images, and one set with varying yaw angles.

1. In the first set, image sizes range from 310 to 1000 pixels in width, and 240 to 1330 pixels in height. Subjects are generally frontal.
2. In the second set, image sizes range from 720 to 5200 pixels in width, and 1080 to 3500 pixels in height. Subjects are generally frontal.
3. In the third set, there are mated sets of images in which the same person rotates to take on different yaw angles while maintaining the same distance from the camera. The images in this set are grayscale.

In order to determine ground truth for the first and second set, we manually find the eye-centers by determining the two points where eyelids meet for each eye and averaging the two points. The distance between the two eye-centers is used as the ground truth inter-eye distance, as shown in Fig. 14. Note that subjects may have properties that make detection of eyelid corners challenging. Examples include drooping eyelids, makeup on the eyes, and long eyelashes. As a result, there may be times when ground truth is imperfect.



Fig. 14. The 2-dimensional inter-eye distance is calculated by averaging the canthi for each eye and taking the distance of the two resulting points. Image from NIST Special Database 32, MEDS.

For the third set, the ground truth for yaw is determined at the time of capture. This set includes images with yaw ranging from -60 to 60 degrees. The reported inter-eye distance should be the same with yaw and without yaw; one possibility for determining the implied 3-dimensional inter-eye distance is dividing the 2-dimensional inter-eye distance by the cosine of yaw. This is shown in Fig. 15.

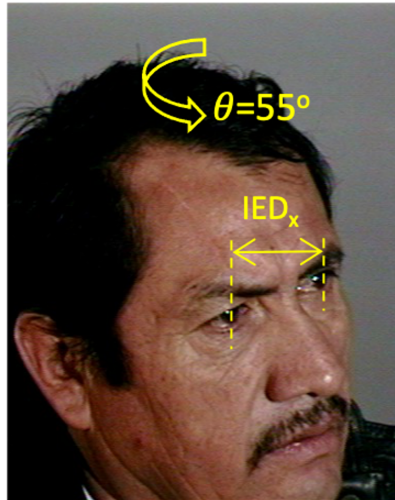


Fig. 15. The 3-dimensional inter-eye distance may be determined by calculating the 2-dimensional inter-eye distance and dividing by the cosine of yaw; $IED_{3D} = IED_x / \cos(\theta_{yaw})$. Image from NIST Special Database 32, MEDS.

3.10.2. Results for Inter-Eye Distance

Table 8, Figure 16, Figure 17, and Figure 18 summarize algorithm performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

Table 8. SIDD InterEyeDistance Mean Absolute Error

Algorithm	IED Set 1	IED Set 2
viante_000	2.8	13.6
secunet_004	3.0	9.8
secunet_003	3.0	10.0
rankone_005	3.4	13.4
dermalog_002	3.6	9.7
roc_006	3.6	17.5
roc_007	3.6	17.5
secunet_001	3.9	25.0
mobbl_000	3.9	9.5
igd_001	3.9	31.1
igd_003	4.0	16.1
secunet_002	4.1	23.4
igd_002	4.3	15.4
frpkauai_000	5.0	20.8
idemia_002	5.7	21.3
neurotechnology_004	6.1	19.1
neurotechnology_002	7.2	12.9
neurotechnology_003	7.2	12.9
digidata_001	10.8	28.6

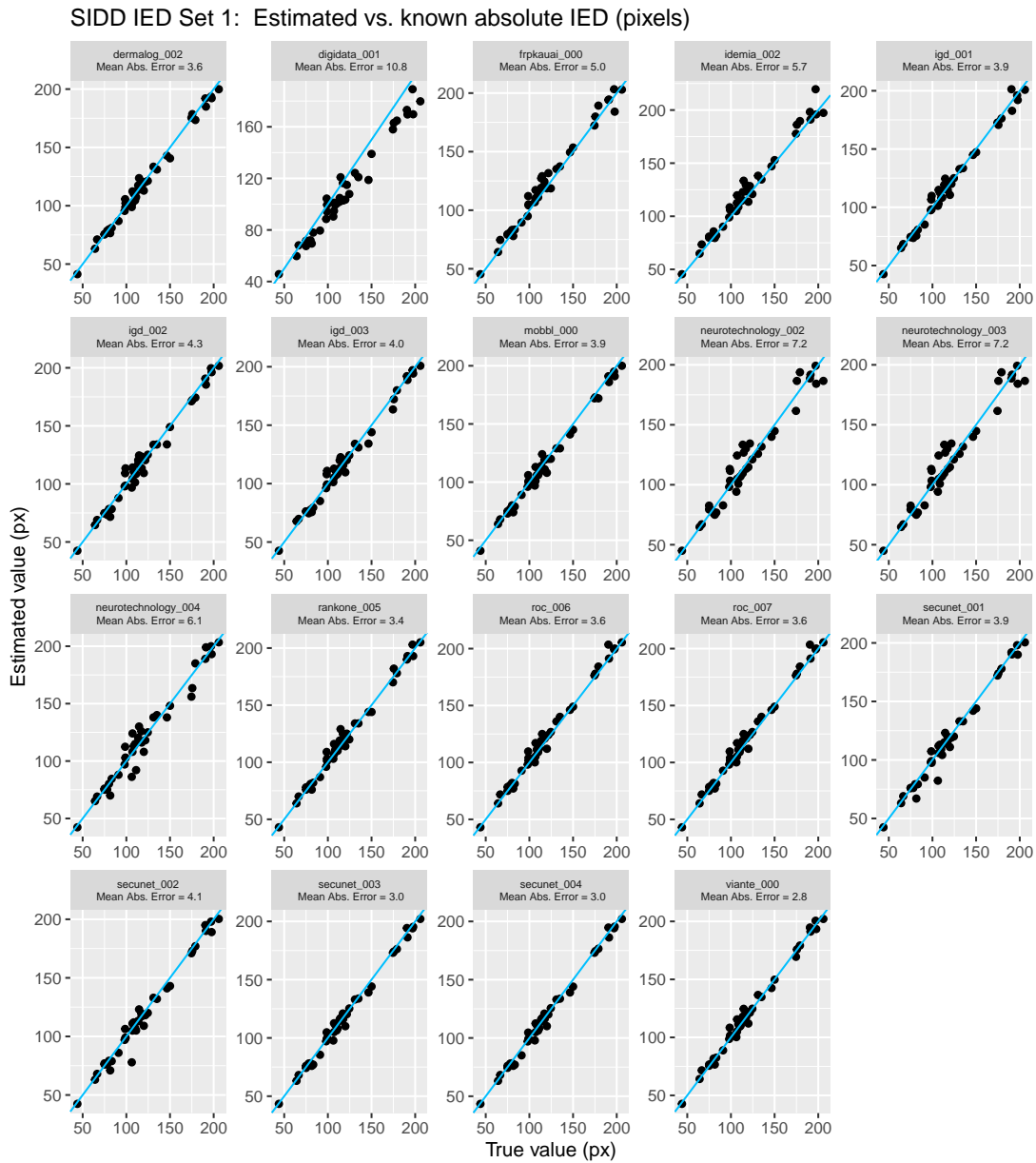


Fig. 16. Estimated vs. known values of inter-eye distance. Ground truth preparation is discussed in Section 3.10.1. The blue line ($y = x$) represents perfect performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

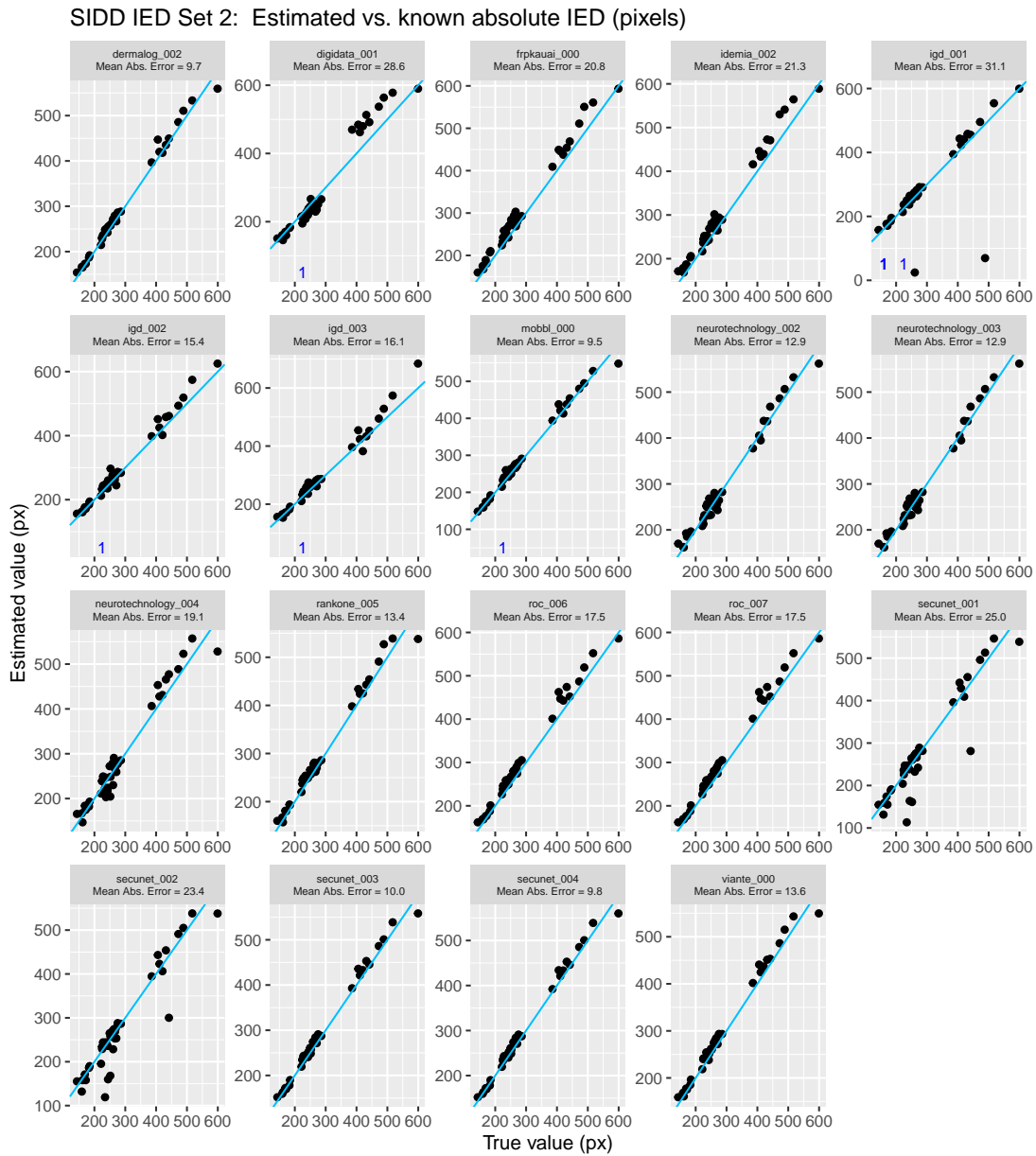


Fig. 17. Estimated vs. known values of inter-eye distance. Ground truth preparation is discussed in Section 3.10.1. The blue line ($y = x$) represents perfect performance. The small blue numbers along the x-axis represent instances when the algorithm did not detect a face; for such images, the error was set to 50. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

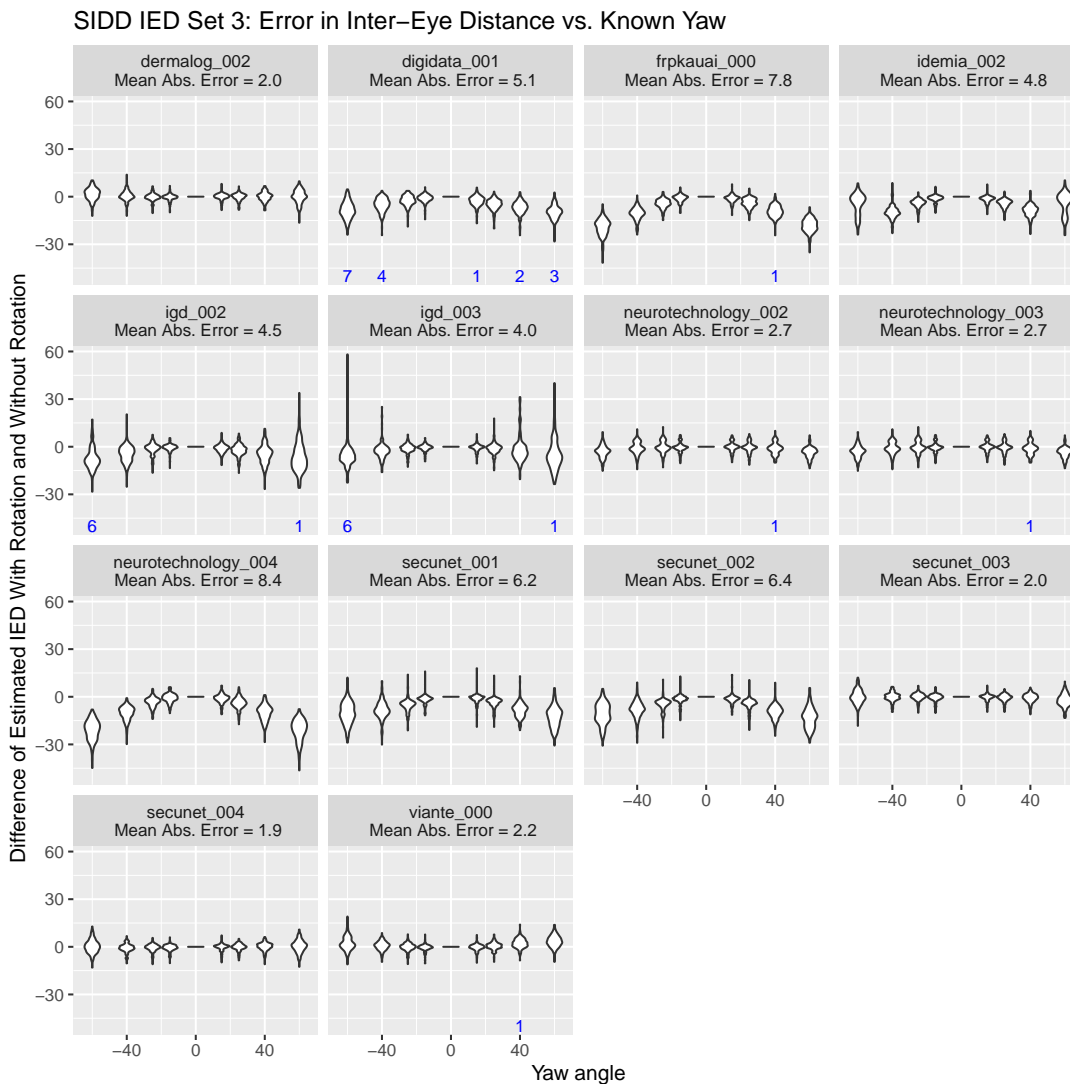


Fig. 18. Difference in reported inter-eye distance (IED) with yaw and without yaw. Perfect performance corresponds to violins centered at $y = 0$ with height 0 across all yaw values. The small blue numbers along the x-axis represent instances when the algorithm did not detect a face; for such images, the error was set to 20. The Mean Absolute Error (MAE), where error is computed as the difference in IED with yaw and IED without yaw for a given capture session, is shown for each algorithm. Lower MAE is better.

3.11. Mouth Open

3.11.1. Images Used

We use mugshot images for the Mouth Open 2 measure. The maximum distance from the bottom of the upper lip to the top of the lower lip is measured, then divided by the inter-eye distance to determine ground truth, as shown in Figure 19. This procedure assigns a ground truth value of zero for mouths that are closed.

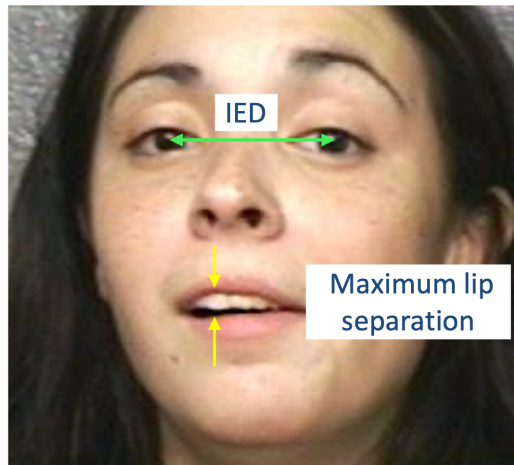


Fig. 19. The MouthOpen measure is computed by taking the maximum distance from the bottom of the upper lip to the top of the lower lip, and dividing the result by inter-eye distance. Image from NIST Special Database 32, MEDS.

3.11.2. Results for Mouth Open

Table 9 and Figure 20 summarize algorithm performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

Table 9. SIDD MouthOpen Mean Absolute Error.

Algorithm	MAE (dimensionless)
neurotechnology_002	0.01
neurotechnology_003	0.01
idemia_002	0.02
secunet_003	0.02
rankone_005	0.03
seamfix_001	0.04
secunet_002	0.04
secunet_001	0.04
digidata_001	0.05
dermalog_002	0.30

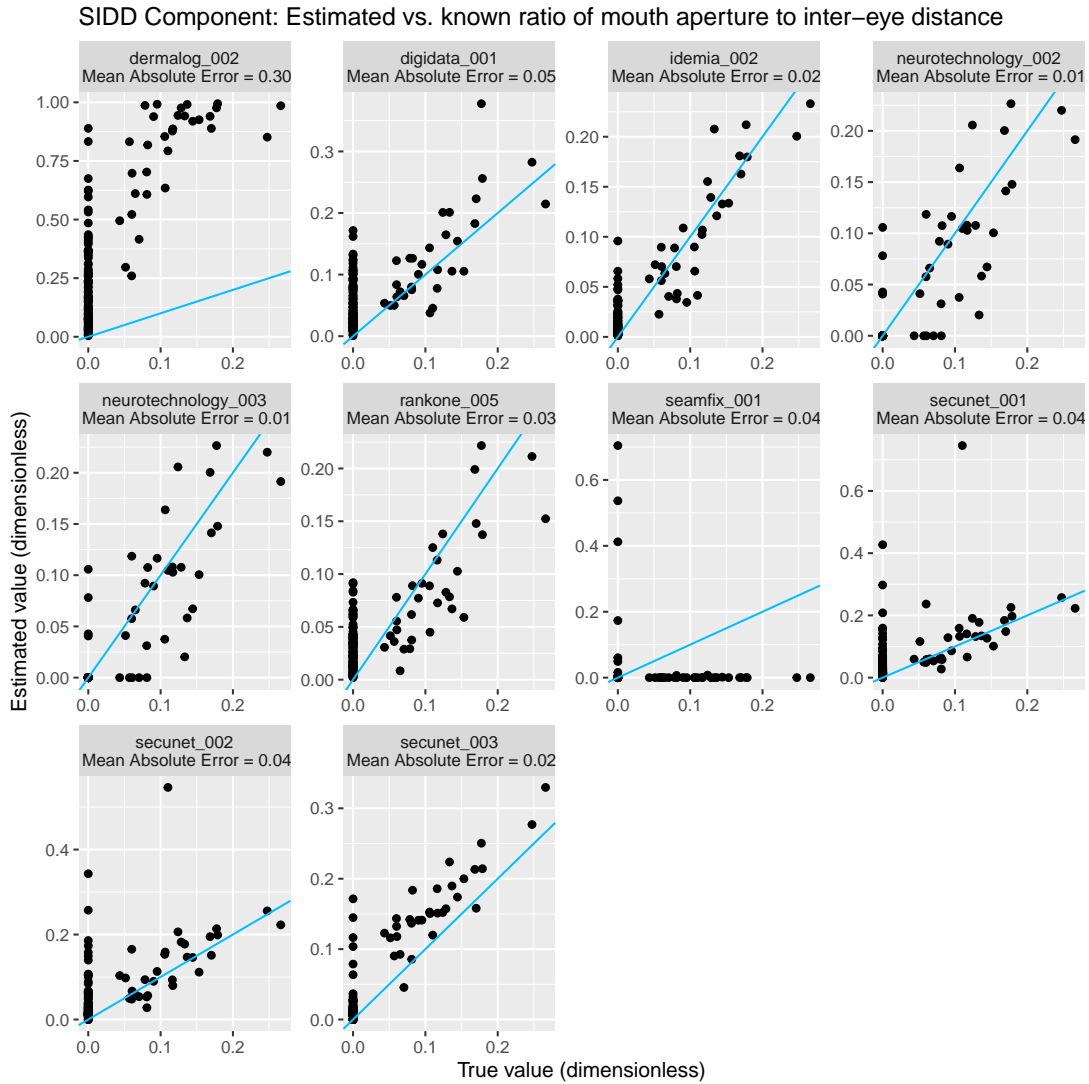


Fig. 20. Estimated vs. known values of the ratio of mouth aperture to inter-eye distance. Ground truth preparation is discussed in Section 3.11.1. The blue line ($y = x$) represents perfect performance. The vertical line of dots at true value zero corresponds to closed mouths.

3.12. Mouth Open 2

3.12.1. Images Used

We use mugshot images for the Mouth Open measure. The maximum distance from the bottom of the upper lip to the top of the lower lip is measured, then divided by the T-metric, the distance from the chin to the midpoint of the eye-centers, as shown in Figure 21. This procedure assigns a ground truth value of zero for mouths that are closed and is consistent with the ISO/IEC 29794-5 standard.

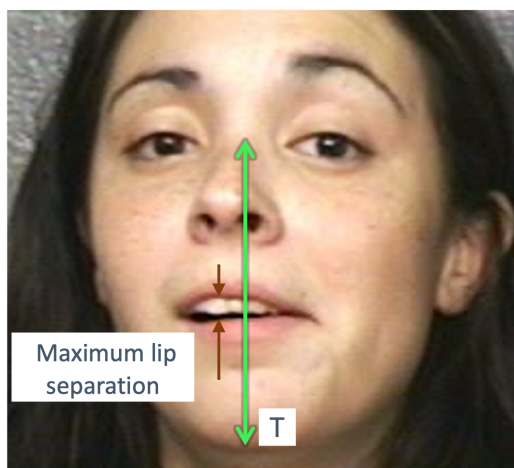


Fig. 21. The MouthOpen2 measure is computed by taking the maximum distance from the bottom of the upper lip to the top of the lower lip, and dividing the result by the T-metric, the distance from the chin to the midpoint of the eye-centers. Image from NIST Special Database 32, MEDS.

3.12.2. Results for Mouth Open 2

Figure 22 summarizes algorithm performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

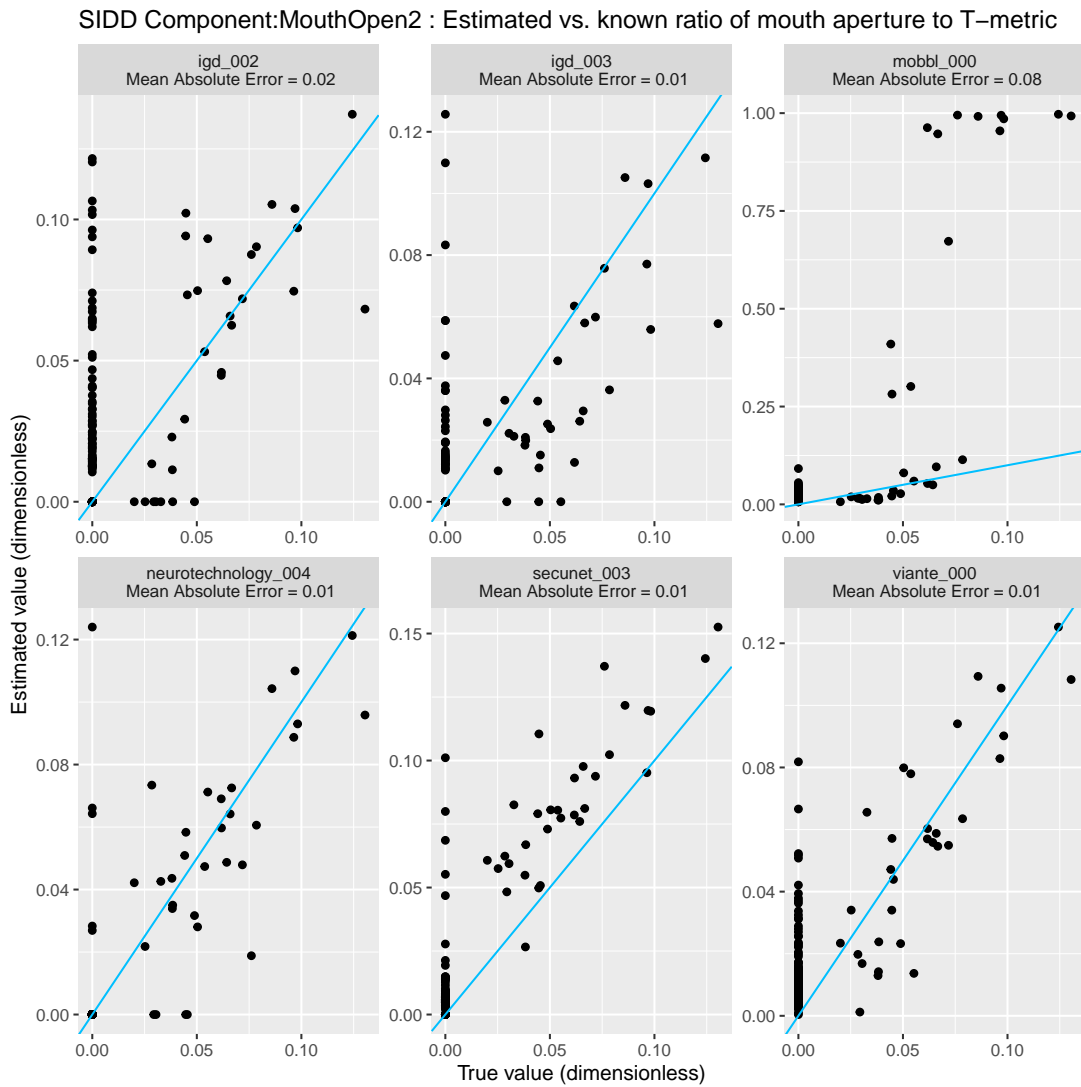


Fig. 22. Estimated vs. known values of the ratio of mouth aperture to T-metric. Ground truth preparation is discussed in Section 3.12.1. The blue line ($y = x$) represents perfect performance. The vertical line of dots at true value zero corresponds to closed mouths.

3.13. Background Uniformity

3.13.1. Images Used

We use mugshot images for the Background Uniformity measure. We categorize images into three categories: Uniform, Attempt at Uniform, and Cluttered.

Uniform images have a plain background, with no brick or shadows behind the subject. Images in the Attempt at Uniform category might have a background with concrete or brick texture. Alternatively, they may have shadows behind the subject, but no other significant non-uniformity. We categorize all other images as Cluttered. The images in the Cluttered category include backgrounds containing furniture, walls with writing behind the subject, and significant variation in background color. Examples are in Table 10.

Table 10. Images in order of increasing background uniformity; the first and third images are used with the permission of the subject. The second image is from NIST Special Database 32, MEDS

Category	Cluttered	Attempt at Uniformity	Uniform
Example			

3.13.2. Results for Background Uniformity

Figure 23 summarizes algorithm performance for background uniformity.

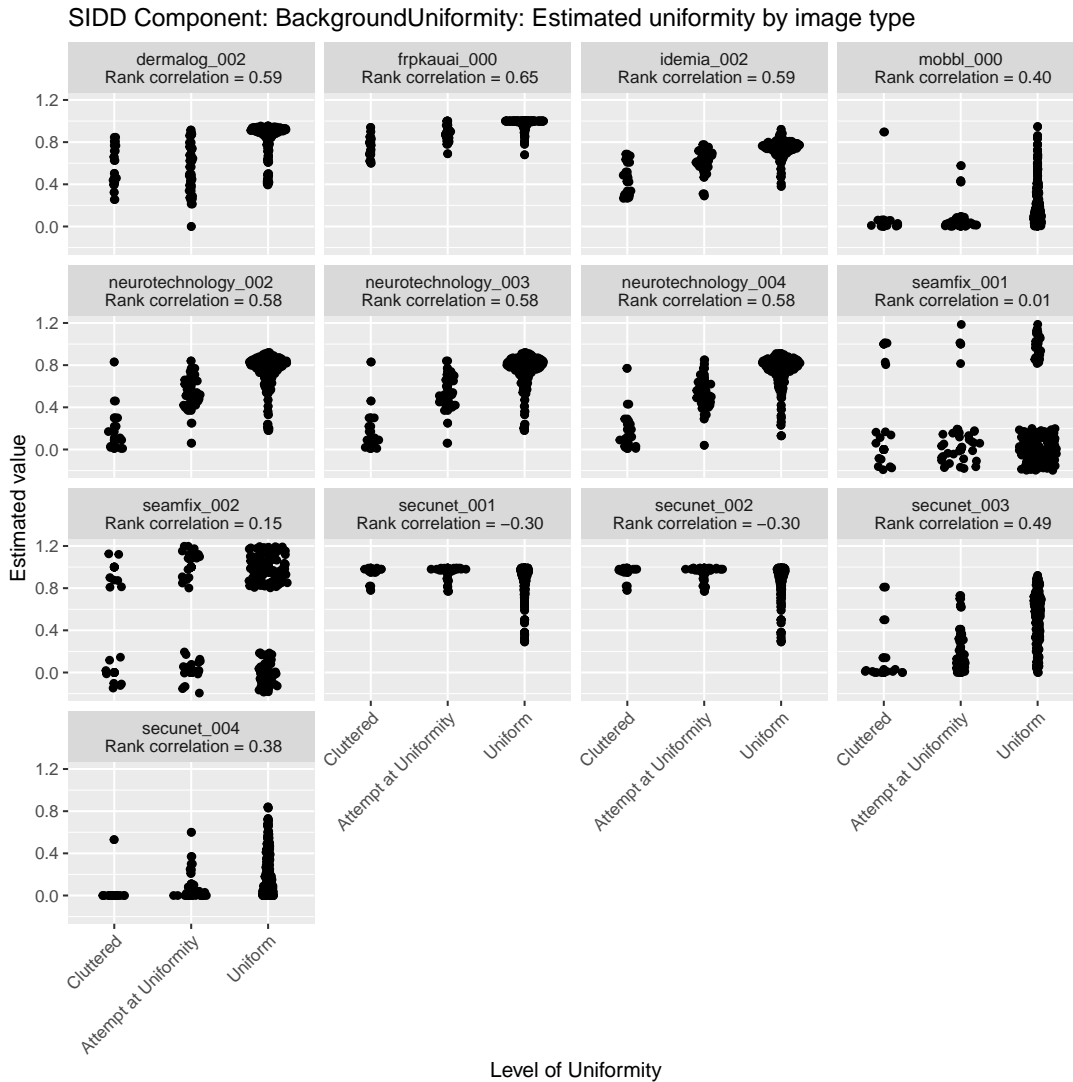


Fig. 23. Estimated degree of background uniformity by category (Cluttered, Attempt at Uniformity, Uniform). Perfect performance corresponds to clusters that shift upward as uniformity increases, and a rank correlation value of 1.




3.14. Resolution

3.14.1. Images Used

The images for the Resolution measure are produced by blurring mugshots. The mugshots are selected to have no significant blur, motion blur, or compression artifacts to begin with. We use the *convert* command from the ImageMagick package with the argument *gaussian-blur*, as illustrated in Table 11. This command convolves each pixel in the input image with a Gaussian kernel. Higher values of the σ parameter, the standard deviation of the Gaussian, correspond to lower resolution.

For the Resolution test, the images range in size from 128 to 3456 pixels in width and 120 to 2719 pixels in height. The inter-eye distance (IED) in the images ranges from approximately 15 to 600 pixels. We use eight values of sigma, ranging from 0 to 7. The highest value of sigma, 7, corresponds to not being able to discern the canthi accurately, but still being able to detect that the eyes are open. Note that the resolution perceived by a reader of this report depends on the handling of the image by LaTeX, the device used to display the image, and other optical factors.

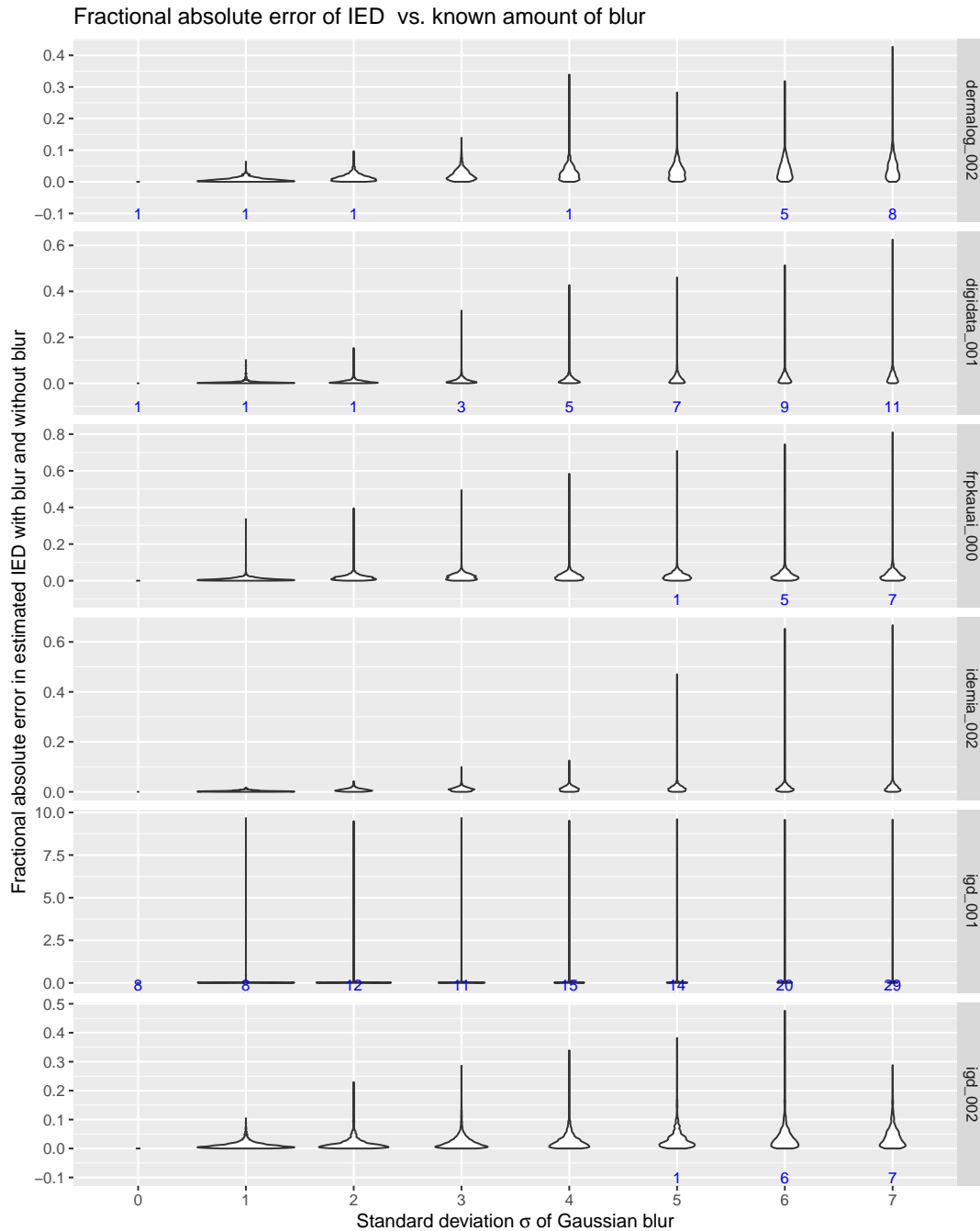
Table 11. Resolution Illustration. Images are used with the permission of the subject.

Standard deviation σ	0	2	5
Result of convert -gaussian-blur 0x σ			

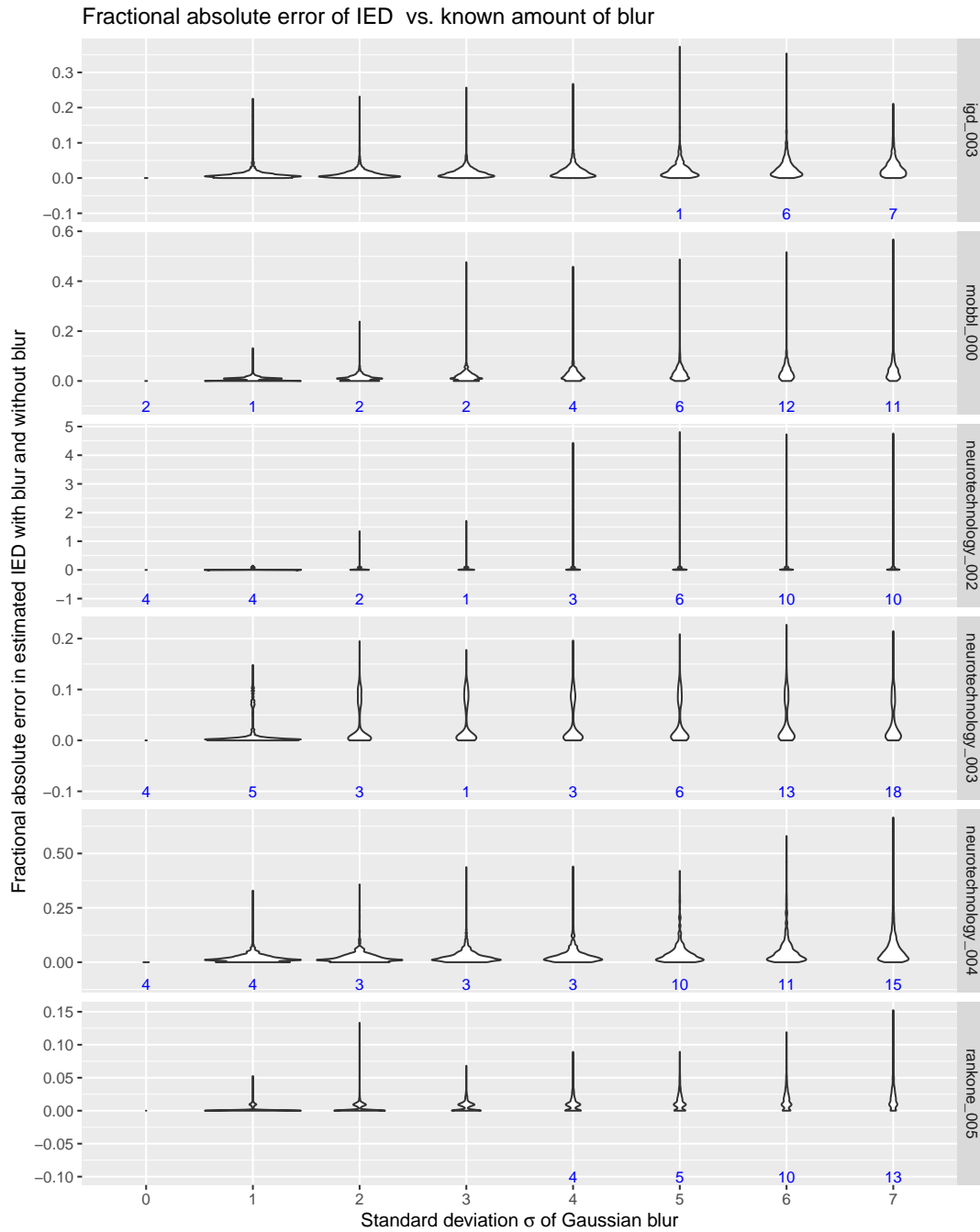
3.14.2. Effect of Gaussian Blur on IED Error

Figure 25 shows a violin plot of the IED error at 8 different values of σ , ranging from 0 to 7. Error is measured with respect to developer-reported IED, so that the error at $\sigma=0$ corresponds to the developer measurement of IED for an original, unblurred image.

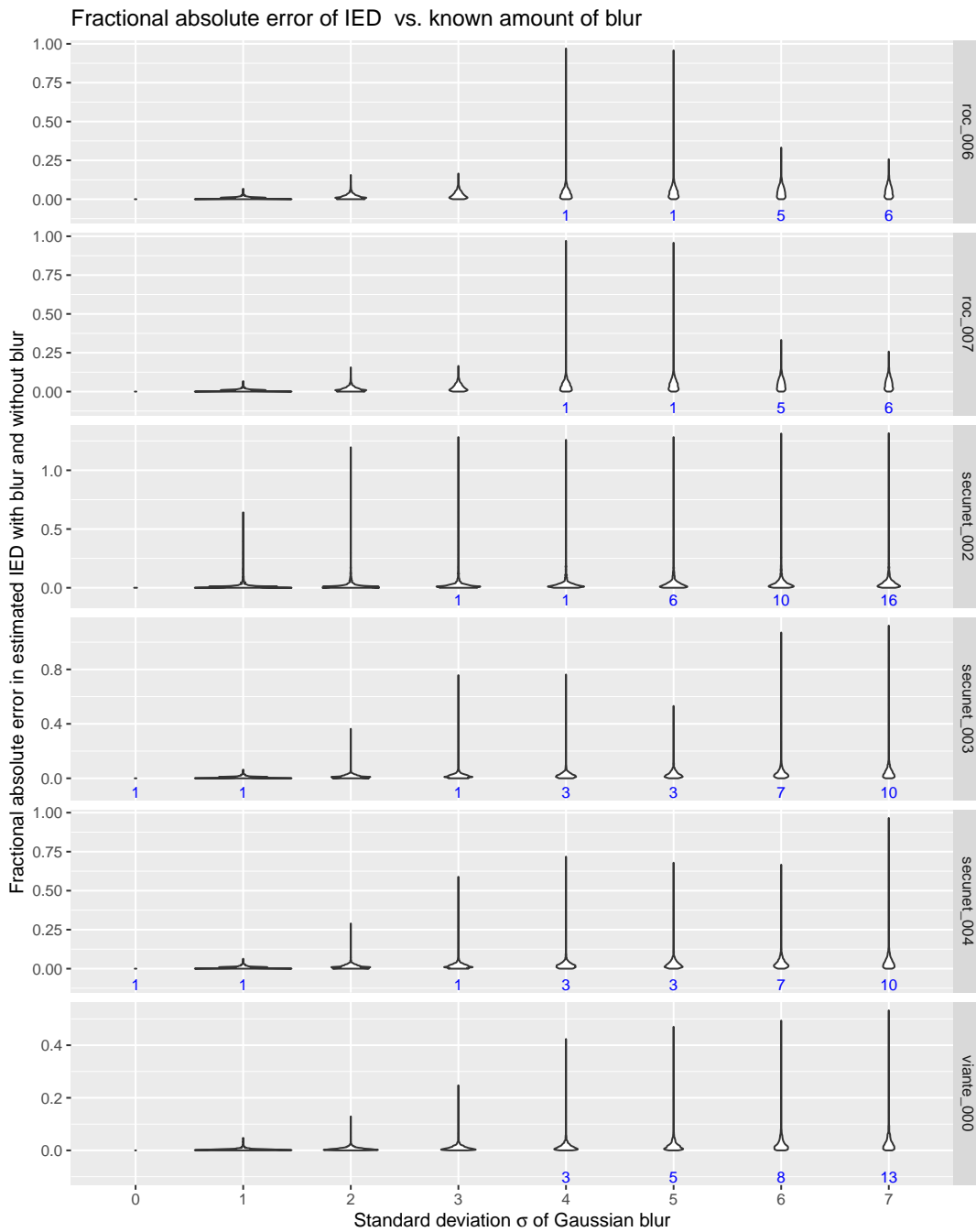
3.14.3. Results for Resolution



(a) Fractional absolute value of error in inter-eye distance estimates vs. σ parameter of Gaussian blur.



(b) Fractional absolute value of error in inter-eye distance estimates vs. σ parameter of Gaussian blur.



(c) Fractional absolute value of error in inter-eye distance estimates vs. σ parameter of Gaussian blur.

Fig. 25. Fractional absolute value of error in inter-eye distance estimates vs. σ parameter of Gaussian blur. The higher the σ , the more extreme the fractional error in IED estimates. The small blue numbers below the x -axis represent the count of images for which the software did not return an estimate, for instance, when it did not detect a face. Note that the plots have different y -axis ranges.

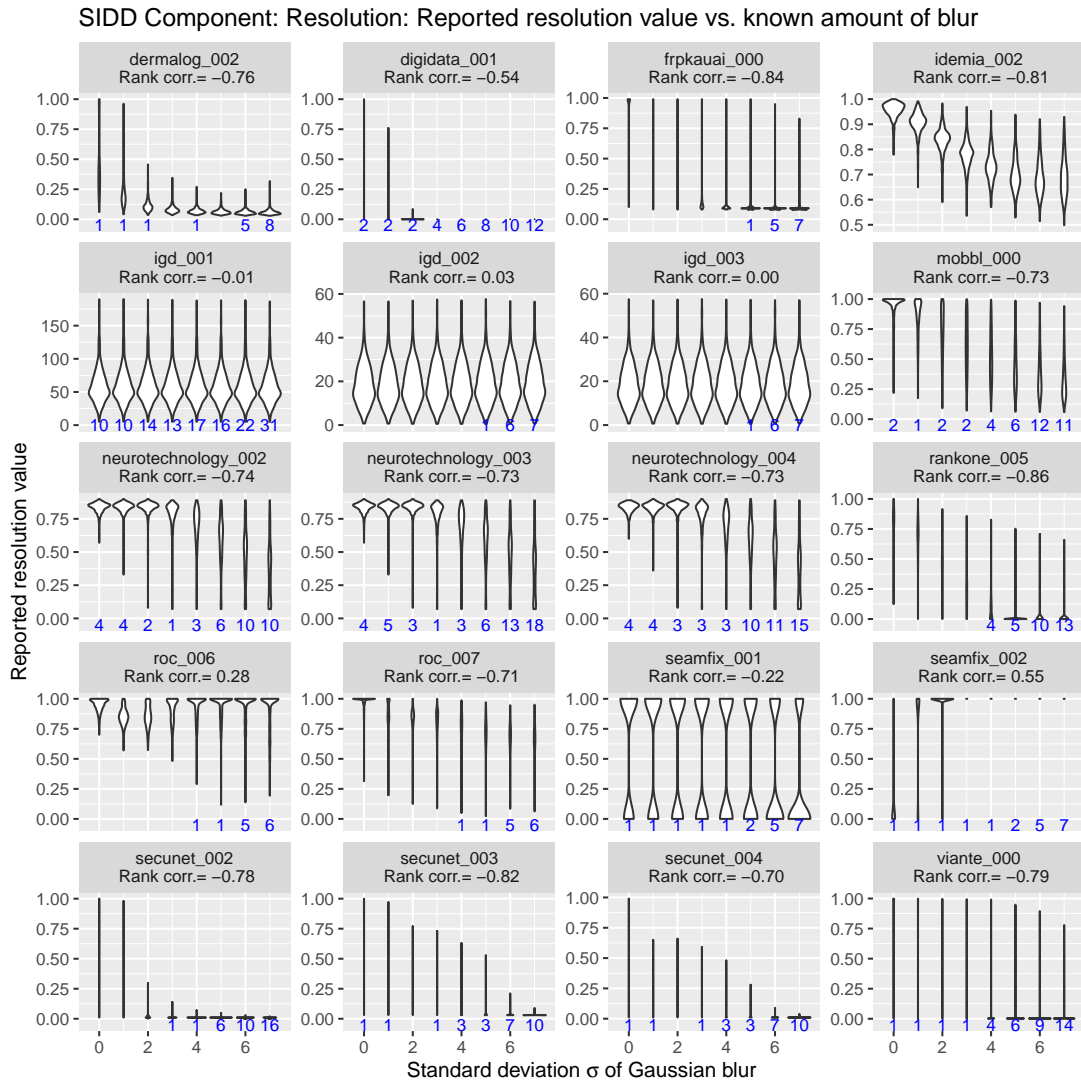


Fig. 26. Distribution of estimated resolution vs. σ parameter of Gaussian blur applied to a set of mugshot images. The higher the σ , the more extreme the blur. The small blue numbers at $y=0$ represent the count of images for which the software did not return an estimate, for instance, when it did not detect a face. Perfect performance would correspond to monotonically decreasing resolution estimates as σ increases, and a rank correlation value of -1 . Note that the plots have different y-axis ranges.


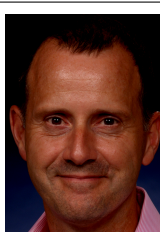

3.15. Underexposure

3.15.1. Images Used

To generate ground truth for the underexposure measure, we start by using mugshot images. We use the *convert* command from the ImageMagick package with argument *brightness-contrast*, as illustrated in Table 12. We use five values of d ranging from 0 to 32. For this measure, more negative values correspond to more underexposure.

Note that the two parameters for brightness and contrast d_1 and d_2 are both inputs, separated by the symbol x . We use $d_1 = -d_2$ to ensure that the two values are inversely proportional and have equal ranges of values.

Table 12. Underexposure Illustration. Images are used with the permission of the subject.

Brightness and contrast (d_1, d_2)	(0,0)	(-16,16)	(-32,32)
Result of convert -brightness-contrast d_1xd_2			

3.15.2. Results for Underexposure

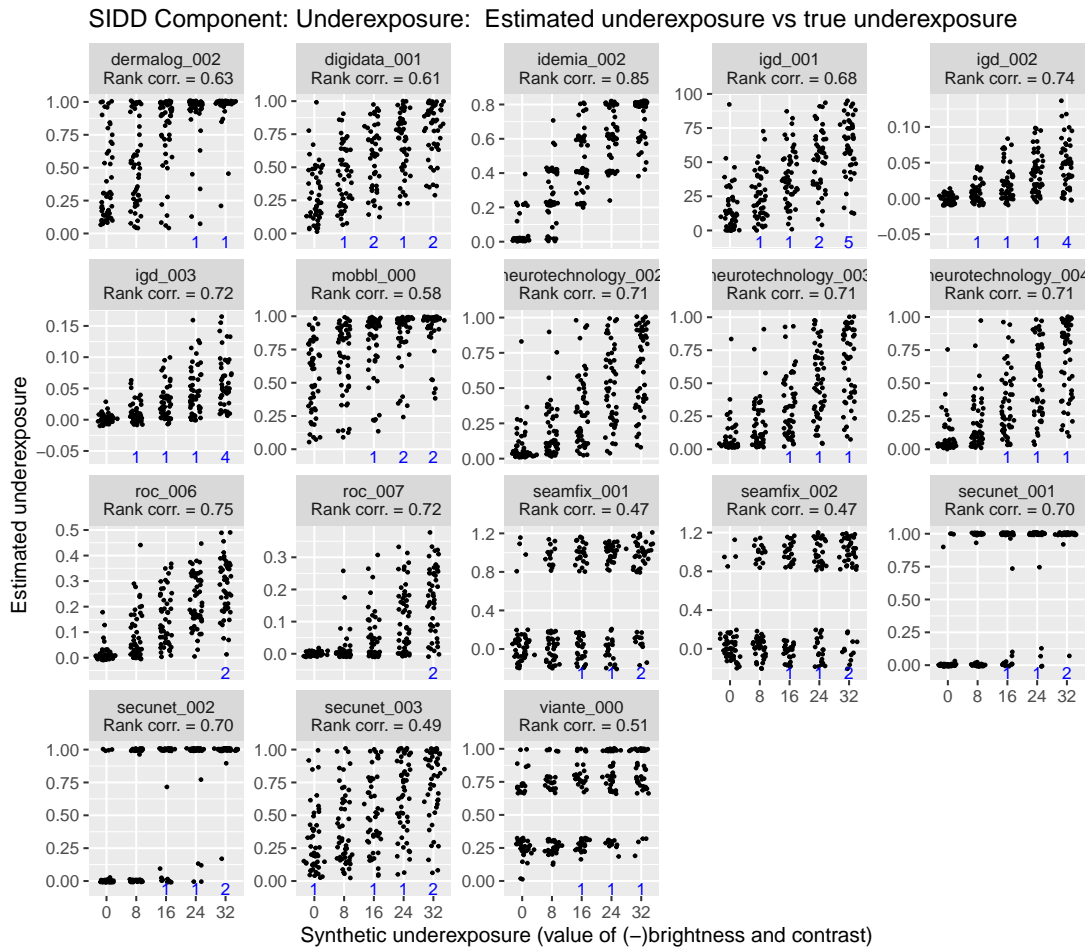


Fig. 27. Distribution of estimated underexposure vs. known underexposure. The x -values represent the contrast and magnitude of decreased brightness of an image. The higher the x value, the more extreme the underexposure. The small blue numbers along the x -axis represent the count of images for which the software did not return an estimate, for instance, when it did not detect a face. Perfect performance corresponds to clusters shifting upward as x increases, and a rank correlation value of 1. The small numbers under the x -axis represent failures to detect a face. Note that the plots have different y -axis ranges.




3.16. Overexposure

3.16.1. Images Used

We start with images from mugshot sets for the overexposure measure. We then use the *convert* command from the ImageMagick package with the argument *brightness-contrast*, as illustrated in Table 13. We use five values of d ranging from 0 to 40. For this measure, higher brightness corresponds to more overexposure.

Note that the two parameters for brightness and contrast d_1 and d_2 are both inputs, separated by the symbol x . We use $d_1 = d_2$ to ensure that the two values increase linearly with each other and lie on the same range.

Table 13. Overexposure Illustration. Images are used with the permission of the subject.

Brightness and contrast (d_1, d_2)	(0,0)	(20,20)	(40,40)
Result of convert -brightness-contrast d_1xd_2			

3.16.2. Results for Overexposure

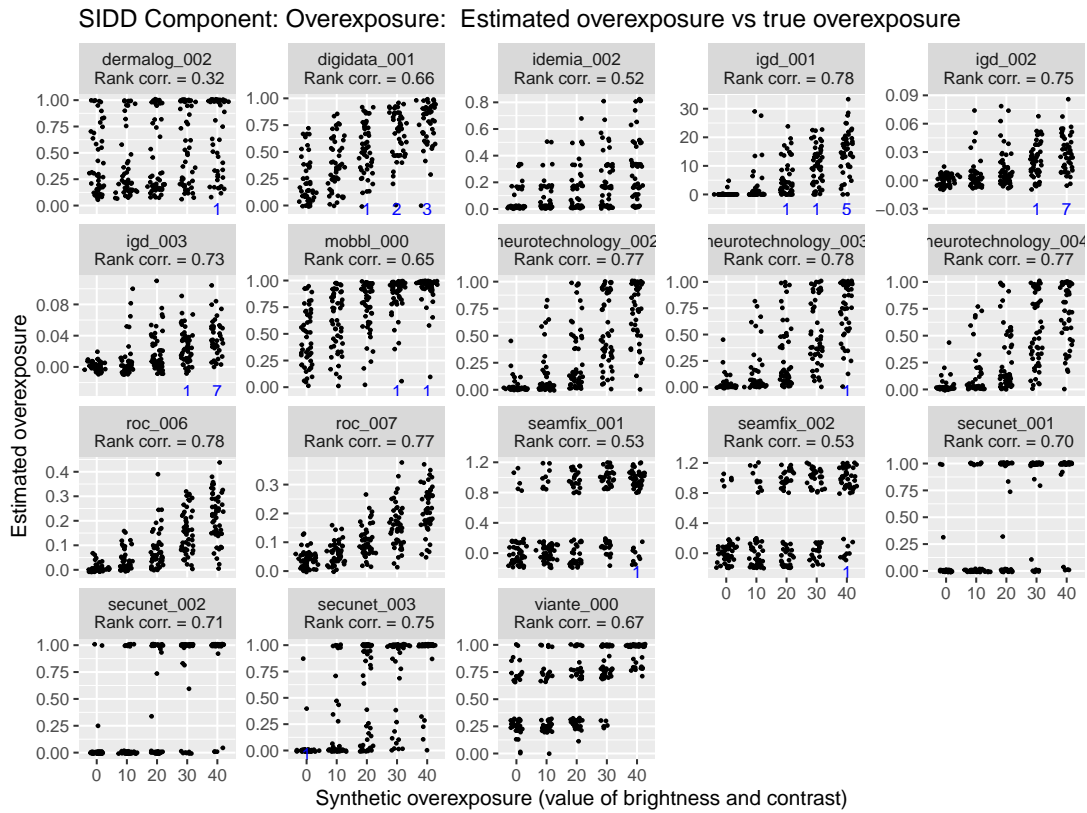


Fig. 28. Distribution of estimated overexposure vs. known overexposure. The x -values represent the contrast and magnitude of brightness applied to an image. The higher the x value, the more extreme the overexposure. The small blue numbers along the x -axis represent the count of images for which the software did not return an estimate, for instance, when it did not detect a face. Perfect performance corresponds to clusters shifting upward as x increases, and a rank correlation value of 1. The small numbers under the x -axis represent failures to detect a face. Note that the plots have different y -axis ranges.

3.17. Eyeglasses Present

3.17.1. Images Used

The images in the Eyeglasses set are mugshot images, in which pose is generally frontal and background is generally uniform. We assign ground truth value of Eyeglasses for images in which the subject is wearing eyeglasses (transparent or sunglasses), and No Eyeglasses otherwise. For our analysis, developers' estimated category is Eyeglasses if the estimated probability of eyeglasses is greater than or equal to a threshold of 0.5, and No Eyeglasses otherwise.

3.17.2. Results for Eyeglasses Present

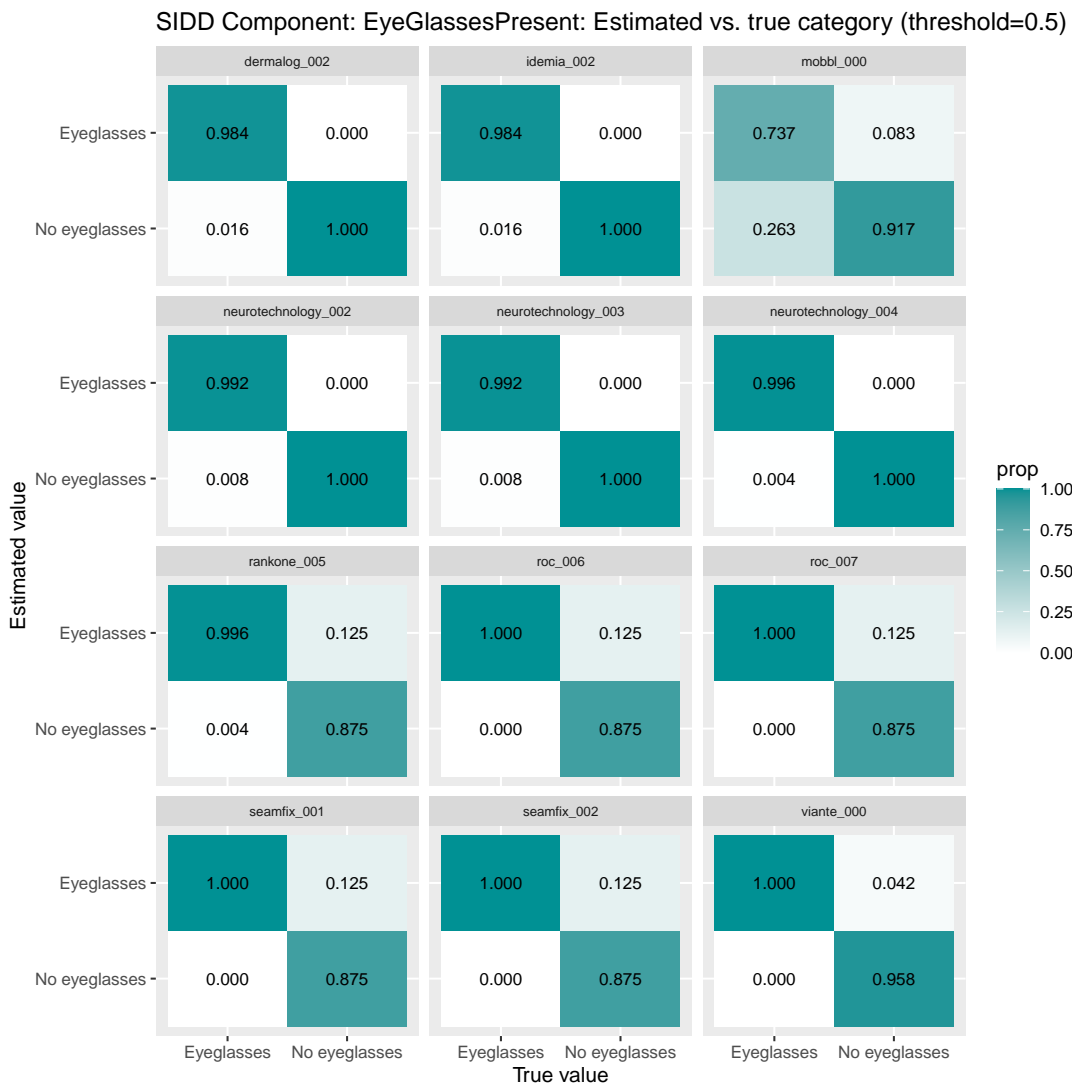


Fig. 29. Estimated vs. known presence of eyeglasses. Perfect performance corresponds to values of 1 at the upper left (for eyeglasses) and the lower right (no eyeglasses), and 0 elsewhere. The values are normalized by the number of images in each category so that each column sums to 1.

3.18. Sunglasses Present

3.18.1. Images Used

The images in the Sunglasses set are images in a natural setting, including non-frontal poses and non-uniform background. We evaluate submissions on images from three categories: opaque, semi-opaque, and transparent.

3.18.2. Results for Sunglasses Present

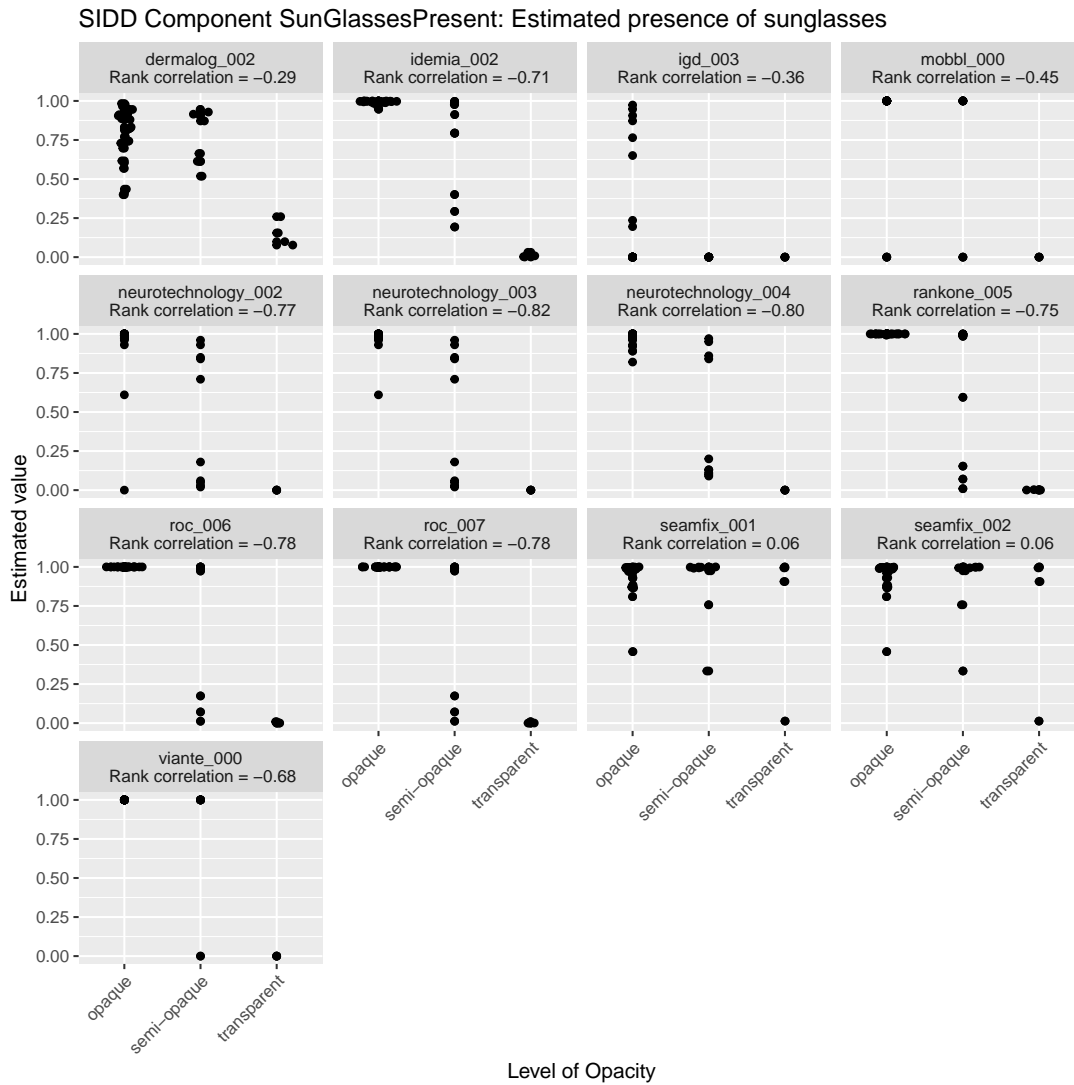




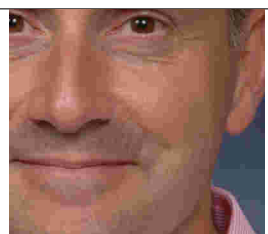
Fig. 30. Estimated vs. known presence of sunglasses. Perfect performance would correspond to monotonically decreasing clusters across the three categories, and a rank correlation value of -1 .

3.19. Compression Artifacts

3.19.1. Images Used

We start by using mugshots for the Compression Artifacts set. We then use the `imageMagick convert` function with the argument `-quality` to apply JPEG compression to the original images. Table 14 shows the effect of blur at three values of compression d .

Table 14. Compression Artifacts Illustration. Images are used with the permission of the subject.

Compression parameter d	90	40	10
Result of <code>convert -quality d</code>			

3.19.2. Results for Compression Artifacts

Figure 31 summarizes the performance of the algorithms who have implemented detection of compression artifacts.

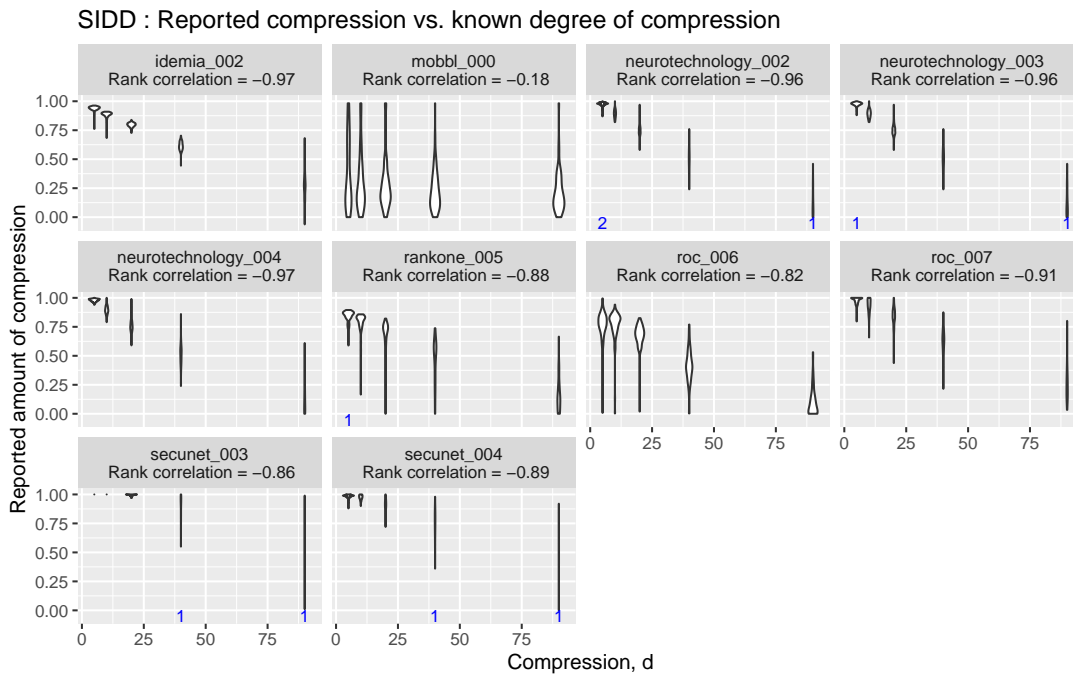


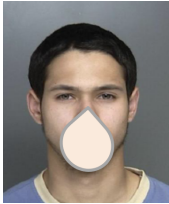



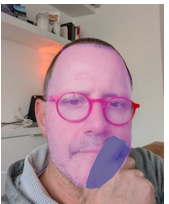

Fig. 31. Distribution of estimated amount of compression vs. d parameter of compression applied to a set of mugshot images. The small blue numbers along the x -axis represent the count of images for which the software did not return an estimate, for instance, when it did not detect a face. The higher the value of d , the lower the compression value. Perfect performance would correspond to monotonically decreasing estimates as d increases, and a rank correlation value of -1 .

3.20. Face Occlusion

3.20.1. Images Used

For the Face Occlusion set, we use images that are generally frontal and well-illuminated. We then compute the occluded area and take the ratio of the occluded area to the total area of the facial region, as described in our [API document](#). Table 15 illustrates values for three example images.

Table 15. Face Occlusion Illustration. The first and third images are from NIST Special Database 32, MEDS; the second image is used with permission of the subject.

Original image			
Image with occluded area shown in blue			
Ratio of occluded area to total area	0.27	0.11	0.36

3.20.2. Results for Face Occlusion

Figure 32 summarizes the performance of the algorithms who have implemented face occlusion.

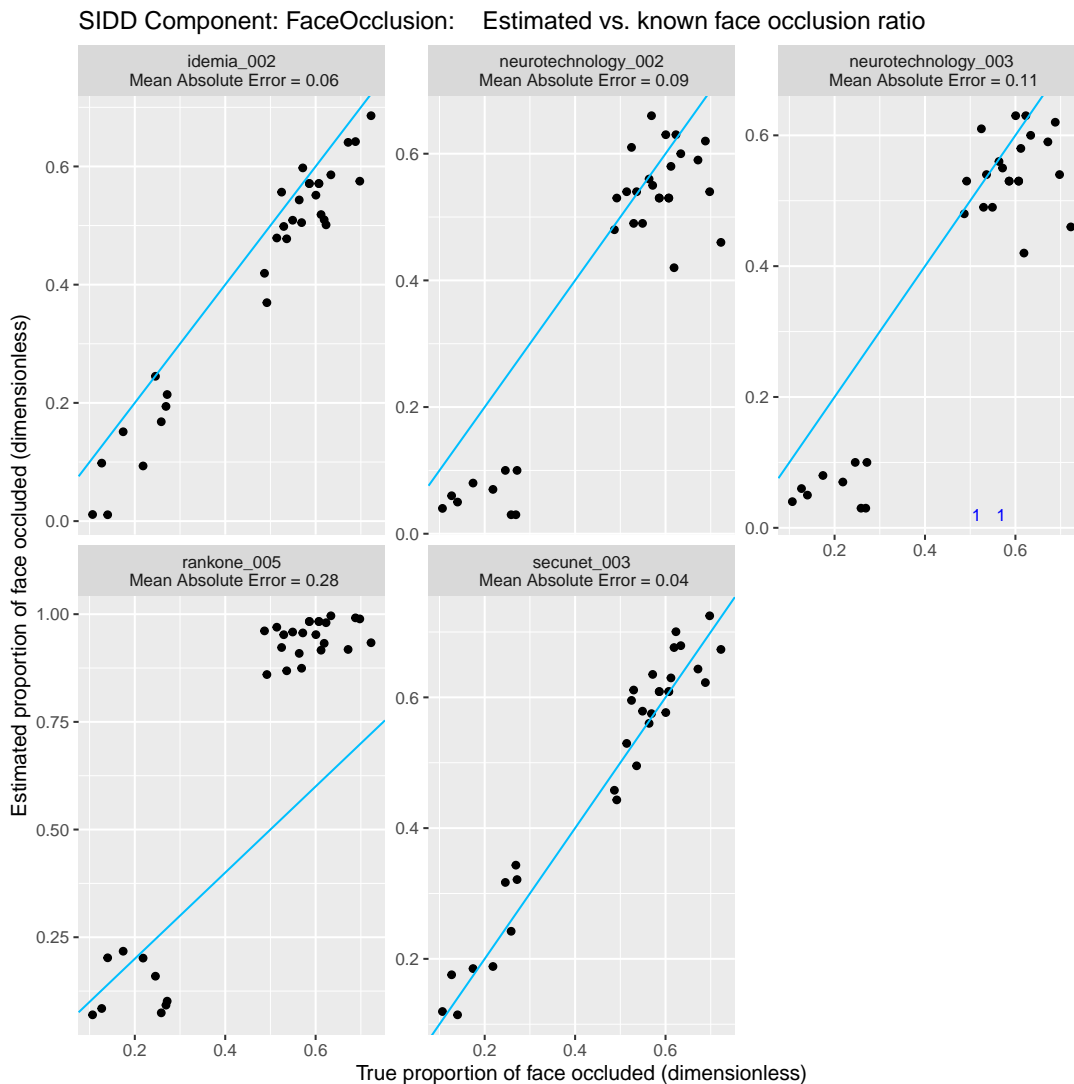


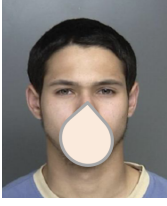



Fig. 32. Estimated vs. known ratio of occluded area to total area of the face. The blue line represents perfect performance. The small blue numbers above the x -axis represent the count of images for which the software did not detect a face; for such images, the error is set to 0.5. Note that the plots have different y -axis ranges. When points fall significantly above or below the blue line, the developer is likely implementing a different definition of the occluded area; for example, including beards or frames of eyeglasses when they should not be considered occlusion.

3.21. Face Occlusion 2

3.21.1. Images Used

For the Face Occlusion 2 set, we use images that are generally frontal and well-illuminated. We then compute the occluded area and take the ratio of the occluded area to the area of the facial region, where the facial region is a convex shape bounded by the eyebrows, chin, and sides of the face, as described in our [API document](#). Note that the facial region does not include the forehead. This definition is consistent with the ISO/IEC 29794-5 standard. Table 16 illustrates values for two example images.

Table 16. Face Occlusion 2 Illustration. Images are from NIST Special Database 32, MEDS.

Original image		
Image with occluded area shown in purple and gray		
Ratio of occluded area (gray) to total area (pink)	0.41	0.22

3.21.2. Results for Face Occlusion 2

Figure 33 summarizes the performance of the algorithms who have implemented Face Occlusion 2.

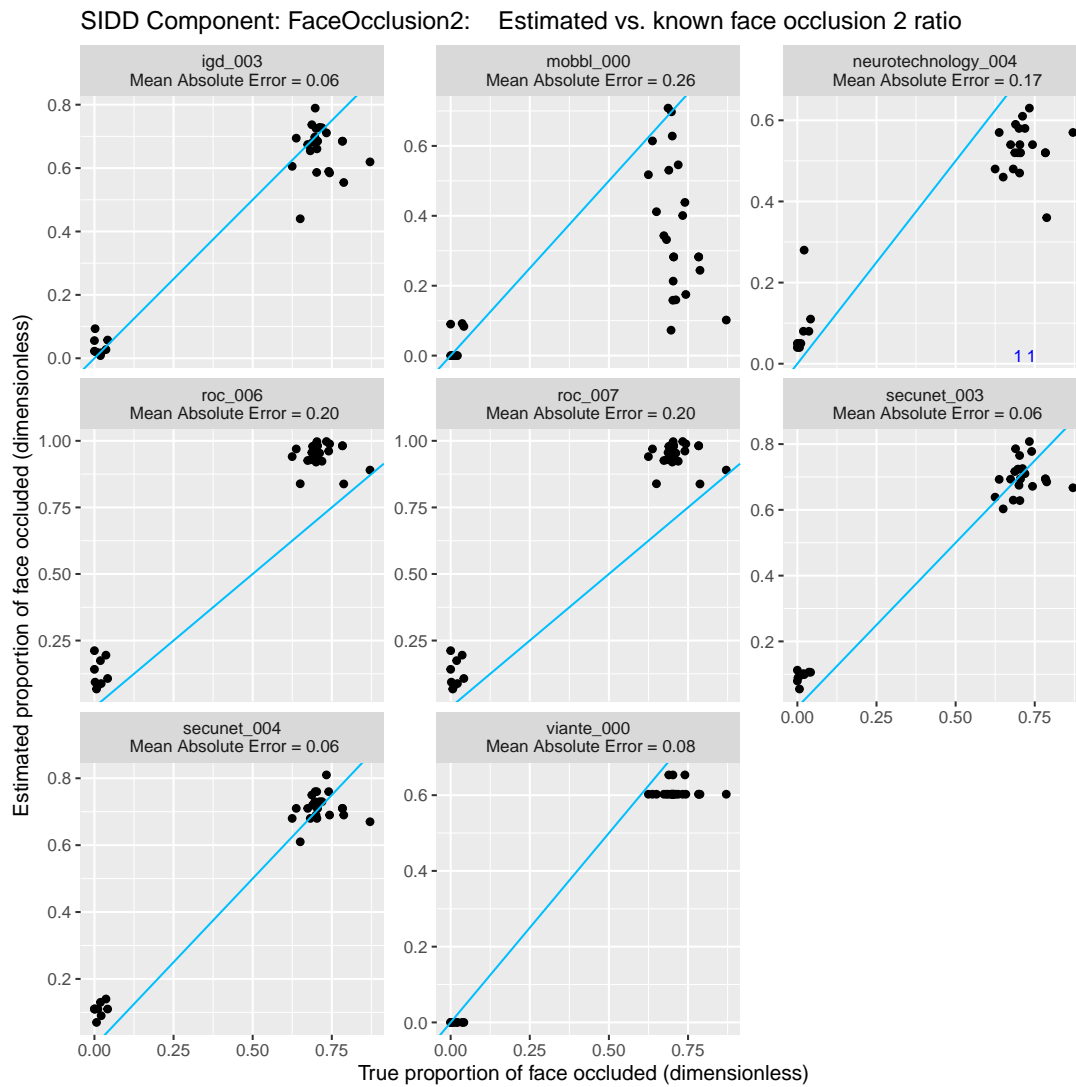





Fig. 33. Estimated vs. known ratio of occluded area to total area of the face. The blue line represents perfect performance.

3.22. Motion Blur

3.22.1. Images Used

We start by using mugshots for the Motion Blur set. We then use the imageMagick *convert* function with the argument *-motion-blur* to apply motion blur to the original images, which are selected to have no visible blur, motion blur, or compression artifacts to begin with. Table 17 shows the effect of blur at three values of displacement d . For our test we use six values of displacement ranging from 0 to 20.

Table 17. Motion Blur Illustration. Images are used with the permission of the subject.

Displacement d	0	8	16
Result of convert -motion-blur 0xd			

3.22.2. Results for Motion Blur

Figure 34 summarizes the performance of the algorithms who have implemented motion blur.

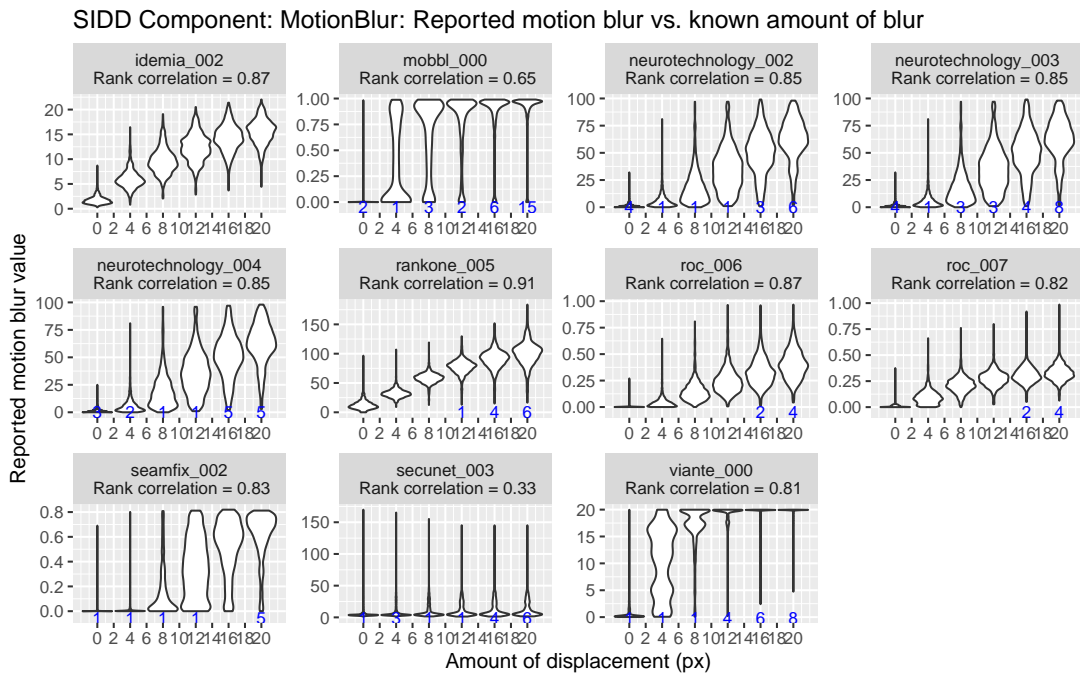


Fig. 34. Distribution of estimated motion blur vs. d parameter of motion blur applied to a set of mugshot images. The higher the value of d , the more extreme the blur. The small blue numbers along the x -axis represent the count of images for which the software did not return an estimate, for instance, when it did not detect a face. Perfect performance would correspond to monotonically increasing estimates as d increases, and a rank correlation value of 1.

3.23. Distance from Eyes to Edges

3.23.1. Images Used

We use mugshots for the four distance-from-eye-to-edge quality measures. Pose is generally frontal and backgrounds are generally uniform. In order to determine ground truth, we manually find the eye-centers by determining the two points where eyelids meet for each eye and averaging the two points. We then calculate the following:

1. The distance from the left edge to the closest eye-center
2. The distance from the right edge to the closest eye-center
3. The distance from the top edge to the average of the eye-centers
4. The distance from the bottom edge to the average of the eye-centers

These quantities are shown in figure 35.



Fig. 35. Image from NIST Special Database 32, MEDS.

This procedure is consistent with that described in the ISO/IEC 29794-5:2024 standard.

3.23.2. Results for Distance from Eyes to Edges

Figure 36, 37, 38, and 39 summarize algorithm performance. The Mean Absolute Error (MAE), where error is computed as the difference between ground truth and reported value, is shown for each algorithm. Lower MAE is better.

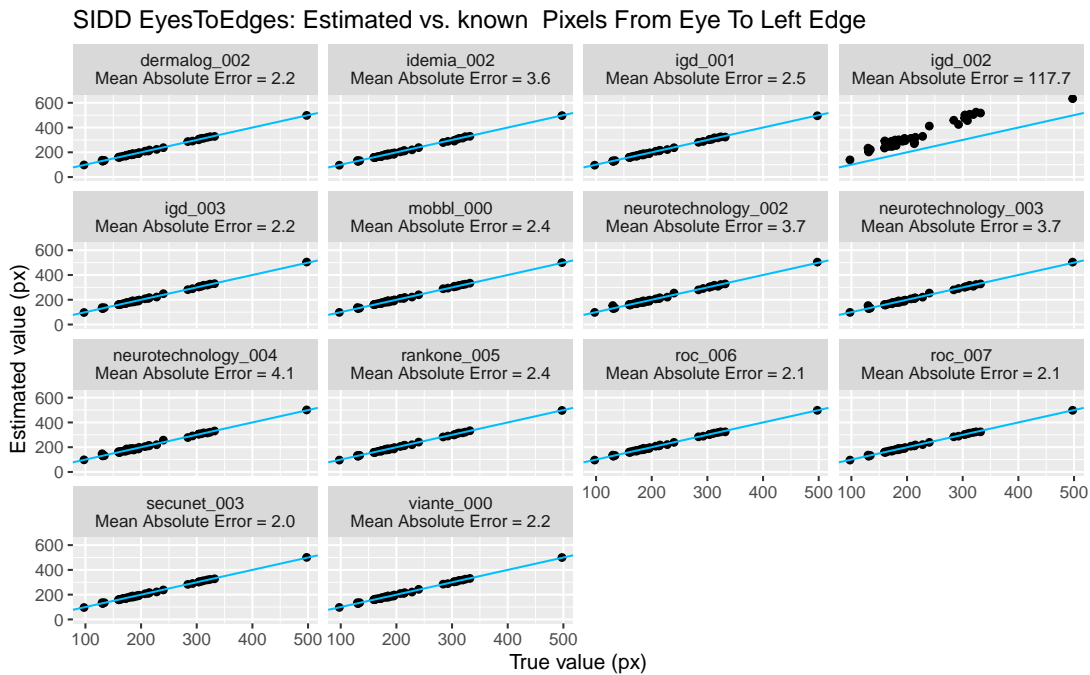


Fig. 36. Estimated vs. known pixels from left edge to the closest eye center. The blue line represents perfect performance.

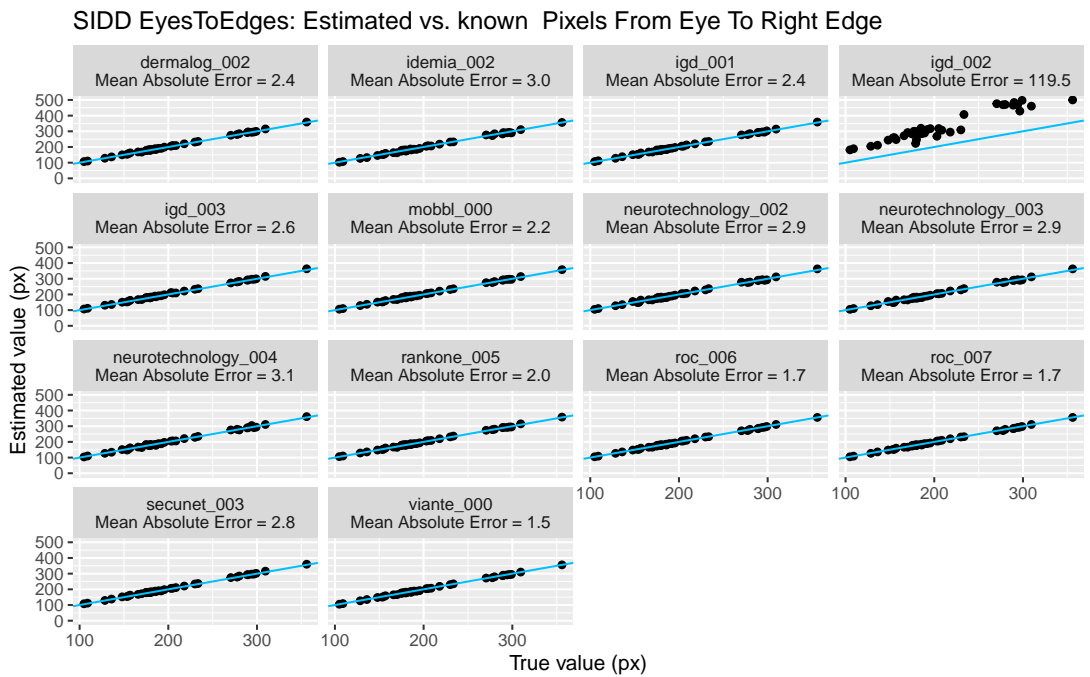


Fig. 37. Estimated vs. known pixels from right edge to the closest eye center. The blue line represents perfect performance.

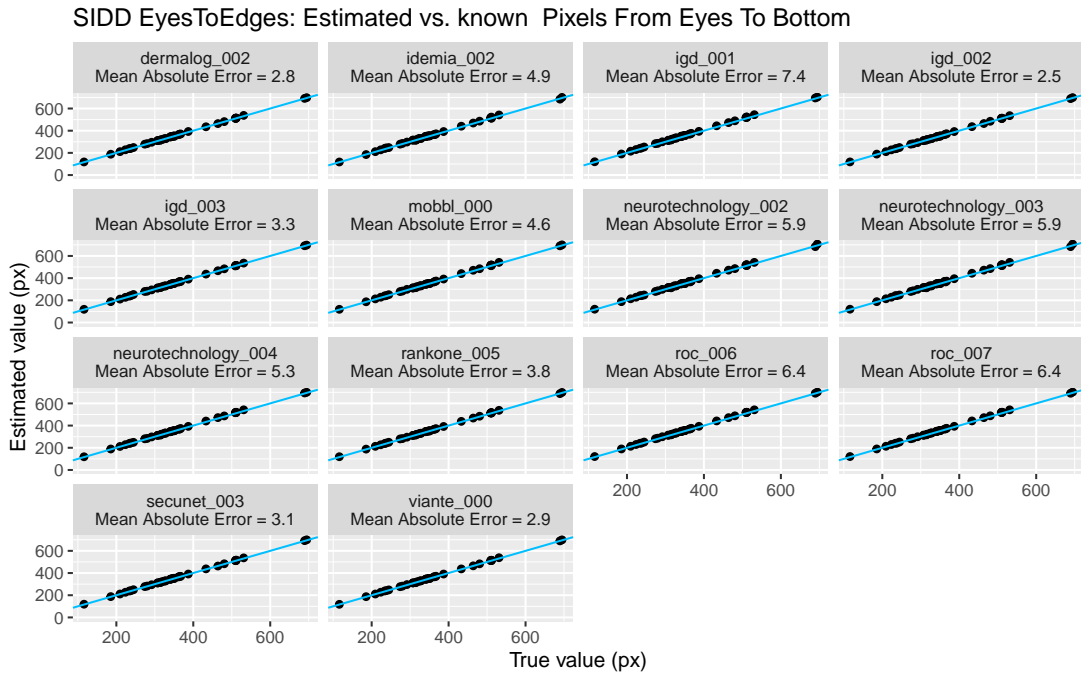


Fig. 38. Estimated vs. known pixels from center of eyes to the bottom of the image. The blue line represents perfect performance.

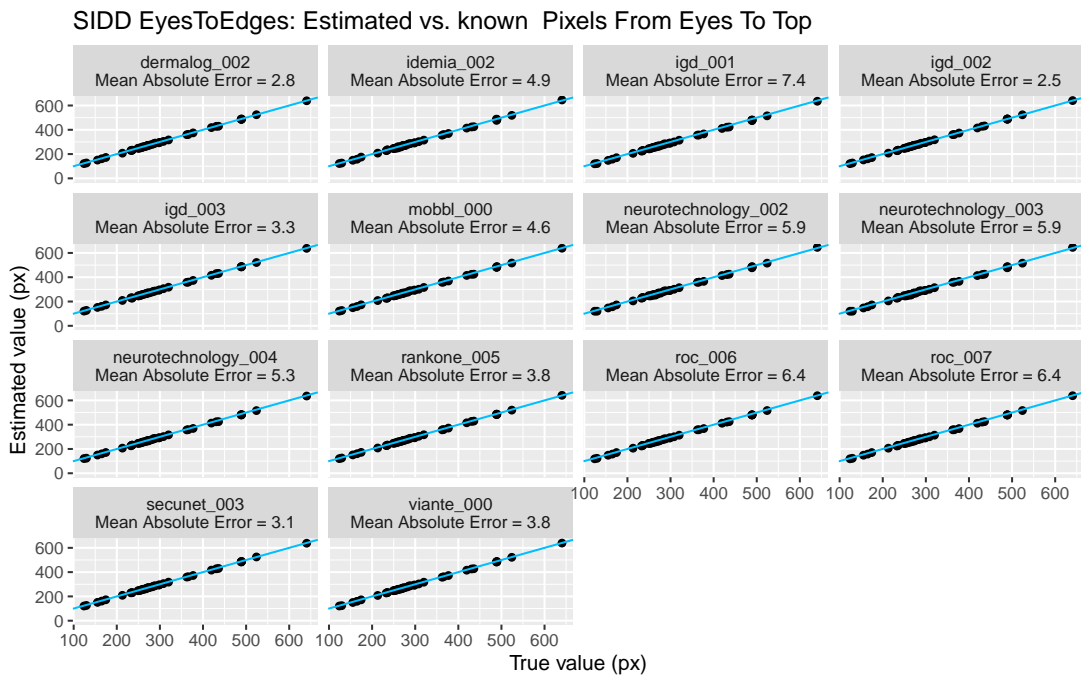


Fig. 39. Estimated vs. known pixels from center of eyes to the top of the image. The blue line represents perfect performance.

3.24. Unified Quality Score

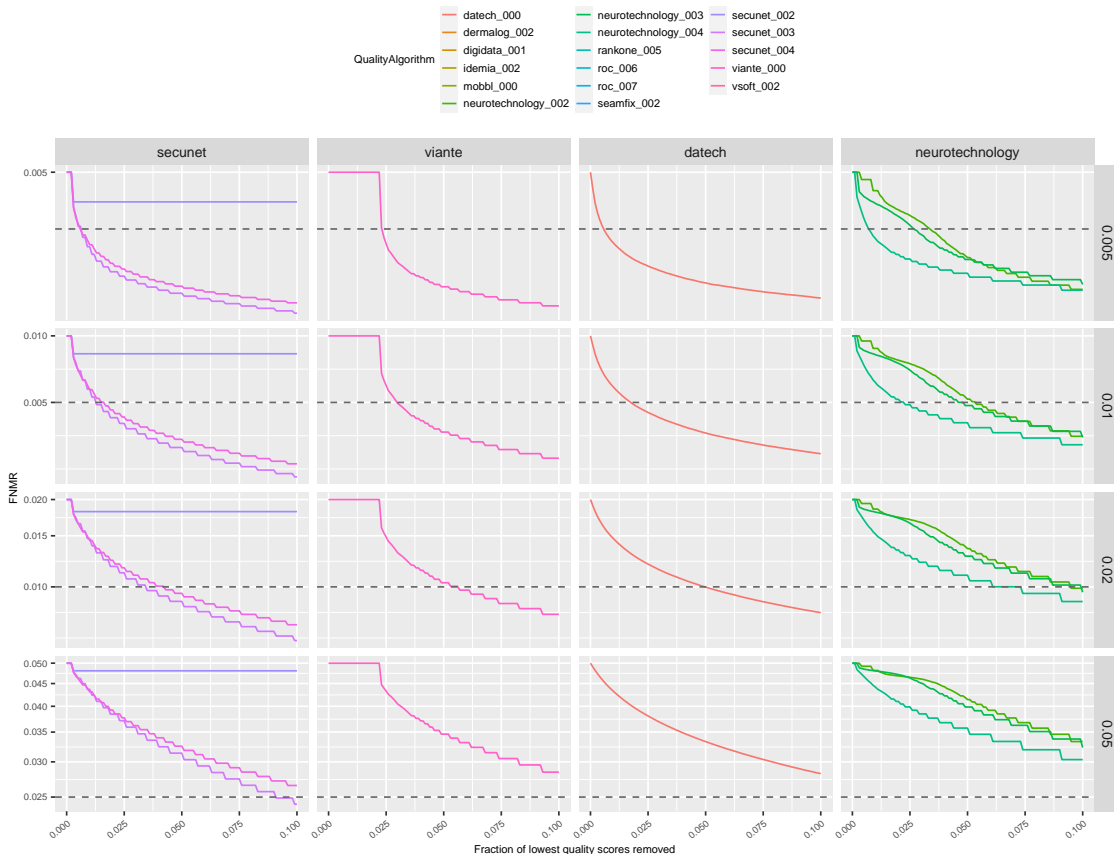
For analysis of Unified Quality Score, we examine the reduction in FNMR as Unified Quality Score is used to discard low quality images. The FNMR values are computed by taking the mean across 15 high-performing recognition algorithms from 15 unique developers.

Similarity scores are generated from mated comparison of high quality visa-like application photos with medium quality airport arrival webcam photos. Quality is computed only on the webcam photos.

3.24.1. Results for Unified Quality Score

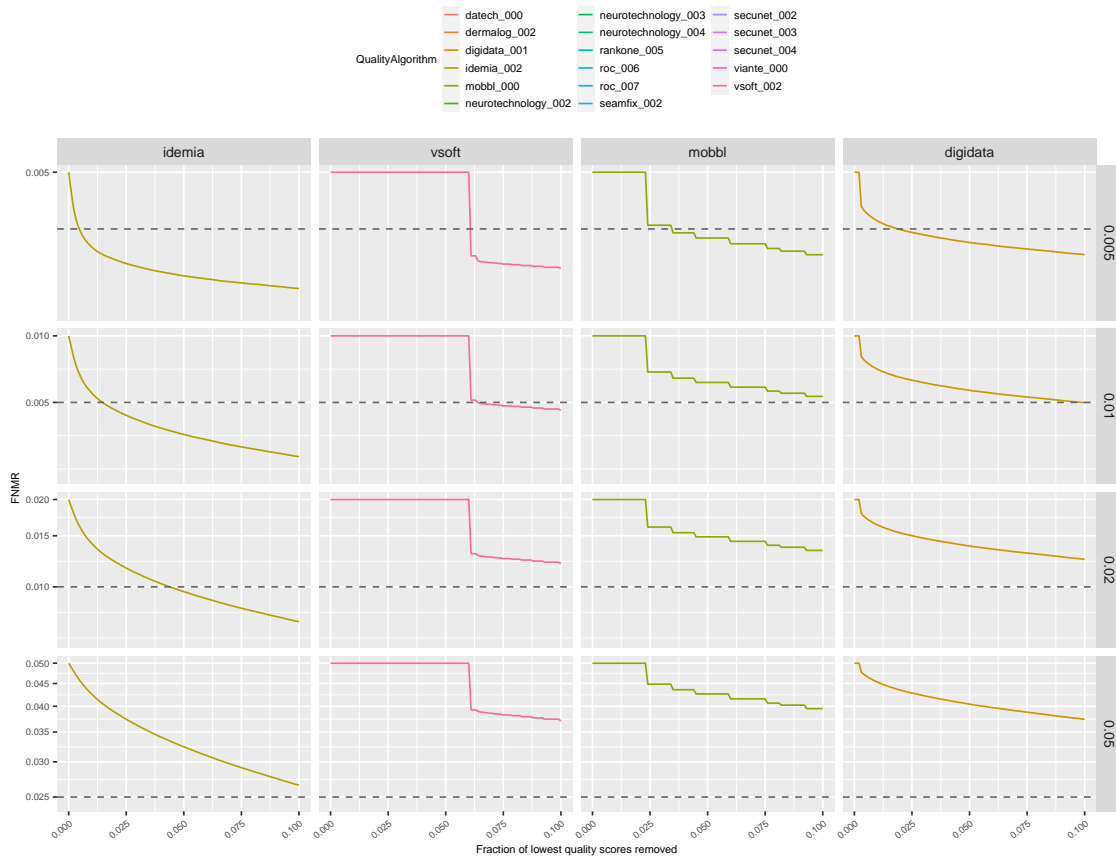
Figure 41 shows false non-match rate (FNMR) gains as a function of the fraction of lowest Unified Quality Score images discarded, for four initial FNMR values: 0.5%, 1%, 2% and 5%.

Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images.



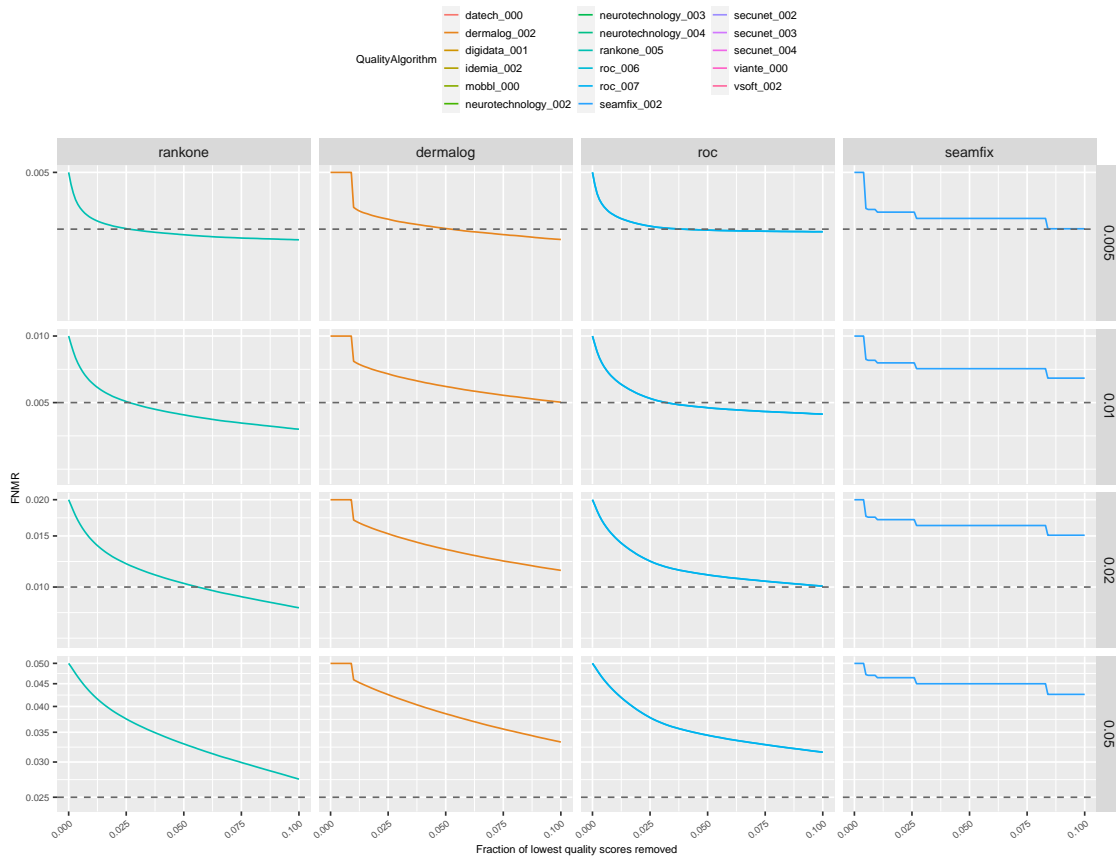
(a) Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images.

Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images.



(b) Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images.

Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images.



(c) Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images.

Fig. 41. Reduction in FNMR as the quality algorithm (QA) is used to discard low quality images. Ground truth for quality is set as the false negatives from 15 of the more accurate recognition algorithms, one per developer. The comparison algorithm's thresholds are set to one of four values corresponding to FNMR = 0.005, 0.01, 0.02, or 0.05 given in the grey row strips. Similarity scores are from mated comparison of high quality visa-like application photos with medium quality airport arrival webcam photos. Quality is computed only on the webcam photos. The dotted line gives either half the initial FNMR, or the lowest observed value. A steeply declining curve connotes a better QA.