https://doi.org/10.2352/ISSN.2470-1173.2020.16.AVM-150

Validation methods for geometric camera calibration

Paul Romanczyk; Imatest, LLC.; Boulder, CO, USA

Abstract

Camera-based advanced driver-assistance systems (ADAS) require the mapping from image coordinates into world coordinates to be known. The process of computing that mapping is geometric calibration. This paper provides a series of tests that may be used to assess the goodness of the geometric calibration and compare model forms:

1. *Image Coordinate System Test: Validation that different teams are using the same image coordinates.*
2. *Reprojection Test: Validation of a camera's calibration by forward projecting targets through the model onto the image plane.*
3. *Projection Test: Validation of a camera's calibration by inverse projecting points through the model out into the world.*
4. *Triangulation Test: Validation of a multi-camera system's ability to locate a point in 3D.*

The potential configurations for these tests are driven by automotive use cases. These tests enable comparison and tuning of different calibration models for an as-built camera.

Introduction

A geometric calibration provides a mathematical model for the pointing direction of each pixel in the camera [1, 2]. The model may or may not have parameters that are tied to physical parameters of the camera system. See Figure 1 for a schematic illustrating a geometric camera model. The black line in this schematic represents the optical axis.

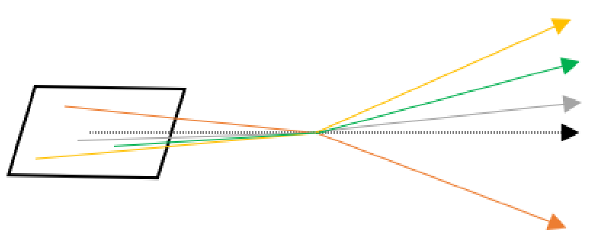


Figure 1. *Schematic illustrating a camera model. Pixel locations map to rays into the world.*

Geometrically calibrating a camera may help overcome manufacturing tolerance limitations to be able to extract more performance out cameras. This can lead to looser manufacturing tolerances allowing for lower cost/higher yield.

A geometric calibration may be used to transform pixel-based metrics to physically based ones. One example extension of a geometric calibration is to compute a world projected modulation transfer function (MTF), *i.e.,* MTF in world units. A second use is computing the instantaneous field of view (IFOV) of each pixel, allowing for photo- or radio-metric calculations.

There are many potential model forms *c.f.* [3, 4, 5, 6, 7, 8]. Once a model is chosen, there are the additional degrees of freedom that are the parameterization of that model. The size of this space make it hard, if not impossible, to create a standard method to produce a geometrically calibrated camera that will meet the ADAS-driven requirements. Additionally the calibration evidence sets and optimization regularization parameters vary from one camera design to another. As a result, we turn to developing validation methodologies to be able to compare camera calibrations of the same camera and ensure that the calibration models will meet the ADAS-driven requirements.

This paper presents four validation methods. The first is a way to validate that the image coordinates agree between two teams. The remainder of the methods are different ways to validate that different models are behaving consistently with camera performance.

Image Coordinate System Validation

There are many possible image coordinate systems that can be used. Some of these are illustrated in Figure 2. Even within the same organization, the image coordinates of the two teams use may not be the same. One of these teams could include the validation team that is collecting and running the other validation tests from later in this paper. Ensuring that teams know the different coordinates of their partners will reduce the chance of problems.

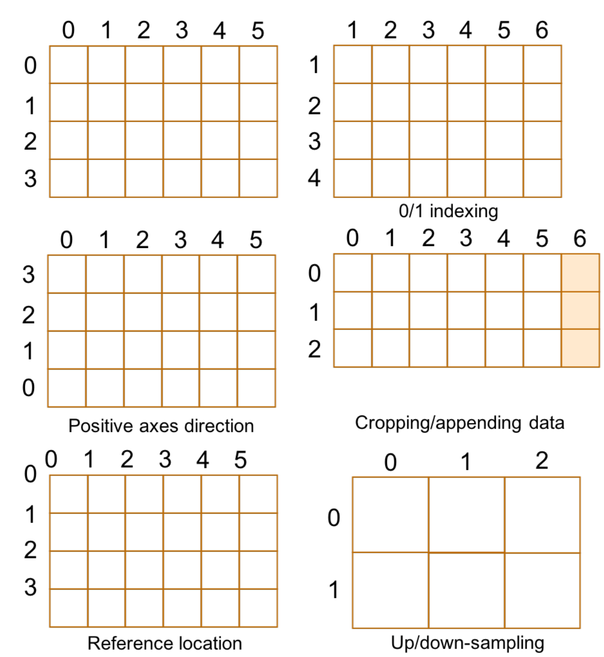


Figure 2. *Possible image coordinate system differences.*

At a minimum, teams should communicate the coordinate system that they use, particularly when describing sensor-relative geometric calibration parameters such as principal point and center of distortion. The remainder of this section will describe an unambiguous test for determining the transforms between different teams' image coordinate system.

Methodology

The methodology makes use of a sensor test pattern. This is intended on being an unambiguous reference coordinate system. Note that not all sensors will have and/or allow access to the required test patterns.

1. Generate a row-index and column-index sensor-test pattern from the sensor through a capture pipeline, *e.g.*, through the production capture pipeline or through an engineering capture system. It is important to turn off the image signal processor (ISP), lest the data be altered in a way that invalidates the test.
2. Between the teams/groups involved, agree on at least 3 non-row and non-column collinear reference points in the test-pattern coordinate system. *I.e.*, there is no more than one test point in each row and each column.
3. Find the location of the reference coordinates in your coordinate system. These are the image data values.
4. Perform an ordinary least squares (OLS) regression on each of the row and column coordinates. The form of the regression is

$$y = m \cdot x + b \tag{1}$$

In most "normal" circumstances, the correlation coefficient will be exactly 1 for these regressions. Additionally, unless there is an up- or down-sampling between the two coordinate systems, the slope of eqn. 1 will be ± 1.

Toy Example

A toy example is presented for two teams coordinate systems with a 6×4 image sensor. See Figure 3 for the marked locations in each coordinate system. The reference sensor coordinates are the color of the pixels, while the team's coordinate systems are given by the pixel location labels. The location of the reference points are listed in the Table captioned "Location of points in toy example".

Location of points in toy example.

Point	Sensor		Team 1		Team 2	
	x	y	x	y	x	y
1	2	1	2	1	3	3
2	3	3	3	3	4	1
3	0	0	0	0	1	4

Performing OLS regressions on the data in Table 1 leads to the coordinate system transforms in the Table captioned "Transforms derived from the toy example test". From inspection of these results, Team 1 is using the sensor coordinates, whereas Team 2 is using a one-indexed coordinate system with a flipped y-axis. Neither of these are necessarily wrong, however care will need to be taken when these two teams communicate.

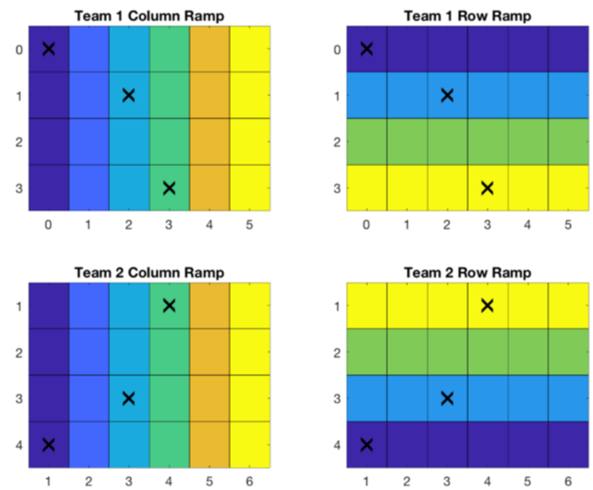


Figure 3. Sample marked points in two teams' coordinate systems.

Transforms derived from the toy example test.

		To		
		Sensor	Team 1	Team 2
From	Sensor		$x_1 = x_s + 0$ $y_1 = y_s + 0$	$x_2 = x_s + 1$ $y_2 = 4 - y_s$
	Team 1	$x_s = x_1 + 0$ $y_s = y_1 + 0$		$x_2 = x_1 + 1$ $y_2 = 4 - y_1$
	Team 2	$x_s = x_2 - 1$ $y_s = y_2 + 4$	$x_1 = x_2 - 1$ $y_1 = y_2 + 4$	

Reprojection Test

The reprojection test projects a target through the forward camera model to compute errors in image space. It is the same methodology as computing the reprojection error during a calibration process. The metric is the distance between the detected and modeled target location. Note that the setup should be separate from any calibration to avoid overfitting. See Figure 4 for a schematic of the reprojection test where the detected and modeled target locations are compared.

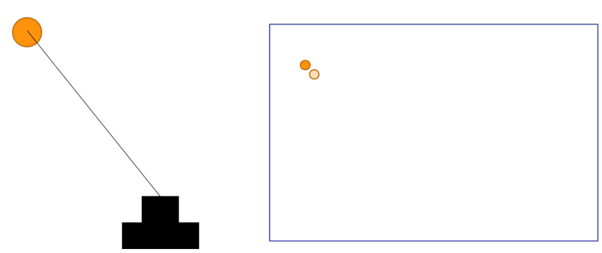


Figure 4. Schematic of reprojection test.

Methodology

1. Create a test setup with targets in the scene.
2. Measure the location of the targets relative to the camera's coordinate system (pose).
3. Take an image of the target(s).
4. Perform detection of the target(s) within the image.
5. Project (image formation direction) the target location (step

2) through the camera model.
6. Compute the error between the detected and projected points in image space (reprojection error).
7. Repeat as needed to ensure test coverage.

Projection Test

Whereas the reprojection test uses the forward or image-forming direction of a geometric calibration model, the projection test test uses the inverse direction by projecting rays out into the world. This is a more natural direction for many calibrations used in ADAS applications. This test assumes that the distance from the camera to a pair of targets is known. Camera-relative world points are computed by projecting target locations through the camera model by the known distance. The test metric is the difference in the distance in the projected world points from the separately measured distance between the targets.

Configurations

There are two classes of configuration of the projection test. The first configuration models the simultaneous localization and mapping (SLAM) use case. This test has either targets narrowly spaced along the direction of travel from a single capture or a pair of captures where the camera moves along the direction of travel. See Figure 5 for an example of this configuration.

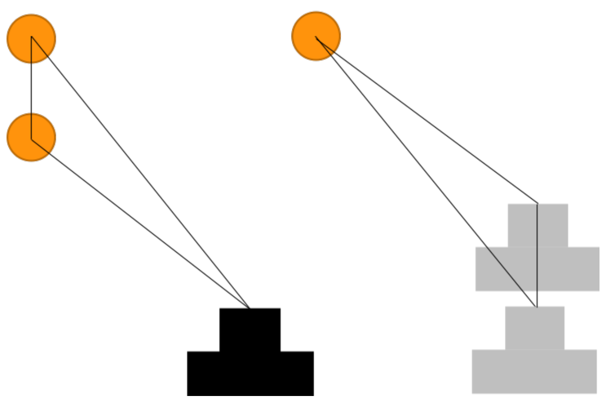


Figure 5. SLAM projection test configuration.

Relative object size is one of the cues that the human visual system uses to determine depth [9]. The second configuration tests the ability to determine object size by "undistorting" the targets. See Figure 6 for an example of this configuration.

Methodology

1. Create a test setup with target pairs in the scene.
2. Measure the distance from the camera to each target.
3. Measure the distance between the target pair(s).
4. Take an image of the target pair(s).
5. Perform detection of the target pair(s) within the image.
6. Project each detected image point out into the world by the distance to target (step 2) to produce a world point.
7. Compute the distance between the projected world points for each pair.
8. Compute the difference in the projected distance (step 7) to the measured target-pair distance (step 3).
9. Repeat as needed to ensure test coverage.

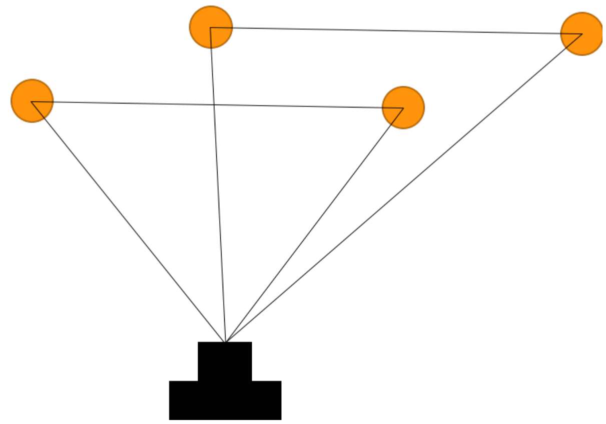


Figure 6. Object size projection test configuration.

Triangulation Test

The triangulation test is similar to the projection test uses the inverse direction of the camera model. The test relies on a single target that is found in each of two cameras. The image locations are then transformed into pointing directions which can be used to triangulate to a world point. The metric is the difference in the triangulated from measured position of the target. See Figure 7 for a schematic of this test.

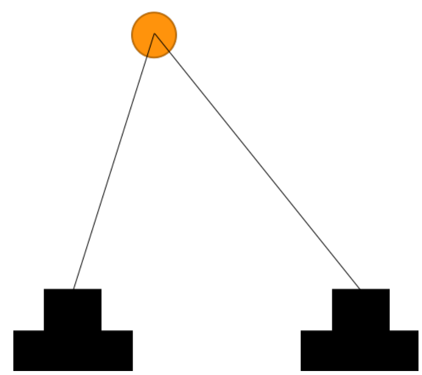


Figure 7. Schematic of triangulation test.

Methodology

1. Create a test setup with target(s) in the scene.
2. Measure the location of the target(s) relative to the reference camera's coordinate system (pose).
3. Take an image of the target(s) with both cameras.
4. Perform detection of the target(s) within the image from each camera.
5. Perform the triangulation of the target(s) using the detected points.
6. Compute the error between the measured location (step 2) and the triangulated location of the target (step 5).
7. Repeat as needed to ensure test coverage.

Validation Test Configurations

To this point, the use of "targets" and positions have been abstract and not defined. This section will detail the target selection and placement within a test scene.

Target Choice

See Figure 8 for a sample of possible targets. The first two targets are a dot and a chessboard intersection. These targets are for when the test does not have access to a full feature detection algorithm, *e.g.*, a convolutional neural network. The reference locations (from which the position/distances are measured) of these two targets are the center of the dot and the chessboard saddle point respectively.

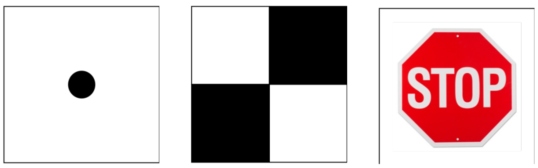


Figure 8. *Possible target choices.*

The third target choice represents an automotive use-case target, such as a stop sign. These targets are intended on being used when testing the entire computer vision system, including the camera and target detection algorithms. The reference location on these targets are the location that which the computer vision system will localize the target, *e.g.*, the intersection of the 'T' in "STOP".

Target Placement

There are two aspects to target placement that need to be considered: the distance to any targets and the distance between the targets. The distance to the targets should be determined by the automotive use-case of the camera. This may be determined in part by solving eqn. 2 for various car velocities and time requirements.

$$d = v \cdot t \tag{2}$$

To make the tests as close to driving conditions as possible, intermediate optics (*e.g.*, collimators) should be avoided for the validation tests.

For the projection test, the separation of targets should also be tied to automotive use cases. The separation for the SLAM configuration should be tied to n frames with a frame time t

$$d = n \cdot v \cdot t \tag{3}$$

The separation of targets for the object-size test configuration should be tied to the sizes of objects encountered in the driving environment. Some of these dimensions are recorded in the Table captioned "Approximate sizes of selected automotive targets."

Target Coverage

The ensemble of tests performed should exercise the entire working field of view. A single test, near the optical axis, will not provide any information on model performance near the edge of the FOV. Coverage can be obtained by filling the field of view with targets and capturing a single image or by having a limited number of targets and capturing with multiple images. For the later configuration, rotating the camera about its center (on-axis entrance pupil position for many camera models) will reduce the setup measurement overhead needed.

Approximate sizes of selected automotive targets. All dimensions are in meters.

Item	L	W	H	Ref.
Compact Car	4.2	1.7	1.5	[10]
Mid-Sized SUV	4.6	1.8	1.7	[10]
Passenger Van	4.6	1.8	1.8	[10]
Large SUV	4.7	1.6	1.7	[10]
Truck, Pickup	5.2	1.8	1.8	[10]
Trailer	14.6	2.6	4.1	[11]
Person, Male, UK		0.36	1.7	[12]
Person, Female, UK		0.37	1.6	[12]
Stop Sign, US	—	varies	varies	[13]

Measurement Accuracy

Determining thresholds for camera goodness should flow down from higher-level ADAS requirements. For example, long-range triangulation may need to be known with in a few meters where close-range triangulation within a few centimeters. These acceptable errors, in turn define how well the position/distances associated with the test are known. The test parameters that can affect the test results are distance/position measurement accuracy and target detection accuracy. It is recommended that an uncertainty analysis [14] be carried out on the test setup to understand how these uncertainties propagate to a test result.

Target Repitition

It is recommended that individual targets at any position not be used. In these configurations, it is impossible to separate measurement error, target detection error, and calibration error. If multiple targets are in very close proximity to each other, the separation of the above errors becomes easier by identifying out-of-family results. See Figure 9 for an example of using multiple targets at each position. The expected errors between any pair of the far-away groups are the same.

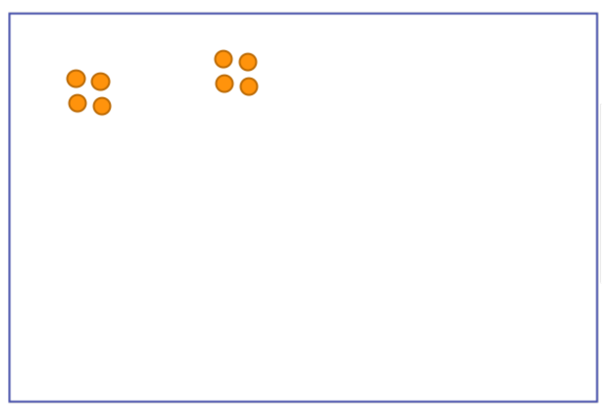


Figure 9. *Example of multiple-target grouping.*

Validation Test Choice

Three different calibration model tests have been presented, each with advantages and disadvantages summarized in Table captioned "Validation Test Summary".

Regardless of which calibration validation test is chosen, the image coordinate system test should always be run as the team

Validation Test Summary

	Reprojection	Projection	Triangulation
Camera Types	Monocam Stereo pair (each) Multicam (each)	Monocam Stereo pair (each) Multicam (each)	Stereo pair
Test Coverage	Intrinsics Distortion Extrinsics	Intrinsics Distortion	Intrinsics Distortion Extrinsics
Required Knowledge	Camera Model Camera Center Camera Pose Target Location(s)	Camera Model Camera Center Distance between Targets Distance to Targets	Camera Model Camera Center Camera Pose Target Location(s)
Advantages	Often used in calibration process	Does not require knowledge of pose Distance measurements easier than position measurements	Evaluates stereo pair use-case
Disadvantages	Not tied to automotive use cases Result goodness tied to pixel pitch Often need to numerically invert the camera model	Uncertainty is deeply coupled with camera model Test does not cover extrinsics	Requires exactly 2 cameras Results tied to triangulation algorihm

performing the validation may use a different coordinate system than the calibration team. This could lead to inadvertently penalizing the calibration produced by a team using a different coordinate system.

Conclusions

This paper presented four geometric calibration validation tests: one for the image coordinate system and three for various combinations of the calibration parameters.

References

[1] R. Hartley and A. Zisserman, *Multiple view geometry in computer vision*. Cambridge University Press, 2000.

[2] Y. Ma, S. Soatto, J. Kosecká, and S. S. Sastry, *An Invitation to 3-D Vision: From Images to Geometric Models*. Springer, 2005.

[3] D. C. Brown, "Decentering distortion of lenses," *Photogrammetric Engineering*, vol. 32, no. 3, pp. 444–462, 1966.

[4] A. E. Conrady, "Decentered lens-systems," *Monthly notices of the Royal Astronomical Society*, vol. 79, pp. 384–390, 1919.

[5] J. Kannala and S. S. Brandt, "A generic camera model and calibration method for conventional, wide-angle, and fish-eye lenses," *IEEE transactions on pattern analysis and machine intelligence*, vol. 28, no. 8, pp. 1335–1340, 2006.

[6] T. Schöps, V. Larsson, M. Pollefeys, and T. Sattler, "Why having 10,000 parameters in your camera model is better than twelve," *arXiv preprint arXiv:1912.02908*, 2019.

[7] P. Sturm, "Multi-view geometry for general camera models," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*. IEEE, 2005, pp. 206–212.

[8] P. Sturm, S. Ramalingam, J.-P. Tardif, S. Gasparini, J. Barreto *et al.*, "Camera models and fundamental concepts used in geometric computer vision," *Foundations and Trends® in Computer Graphics and Vision*, vol. 6, no. 1–2, pp. 1–183, 2011.

[9] S. E. Palmer, *Vision science: Photons to phenomenology*. MIT press, 1999.

[10] automobiledimension.com, "Automobile dimensions," 2020, [Online; accessed 01–Feb–2020]. Available: https://www.automobiledimension.com/

[11] YRC Freight, "Trailer dimensions," 2020, [Online; accessed 01–Feb–2020]. Available: http://yrc.com/trailer-dimensions/

[12] First In Architecture, "Average male and female dimensions/heights," 2020, [Online; accessed 01–Feb–2020]. Available: https://www.firstinarchitecture.co.uk/average-male-and-female-dimensions/

[13] U.S. Department of Transportation, "Standard highway signs manual, 2004 metric edition," 2004, [Online; accessed 01–Feb–2020]. Available: https://mutcd.fhwa.dot.gov/SHSm/regulatory.pdf

[14] Wikipedia contributors, "Propagation of uncertainty — Wikipedia, the free encyclopedia," 2020, [Online; accessed 01–Feb–2020]. Available: https://en.wikipedia.org/w/index.php?title=Propagation_of_uncertainty&oldid=934444035

Author Biography

Paul Romanczyk received both his BS and PhD in Imaging Science from Rochester Institute of Technology (2009, 2015). He has previously worked at the Eastman Kodak Company and the Aerospace Corporation. He is currently a Senior Imaging Scientist at Imatest, LLC. where he develops tests for assessing image quality and camera performance.

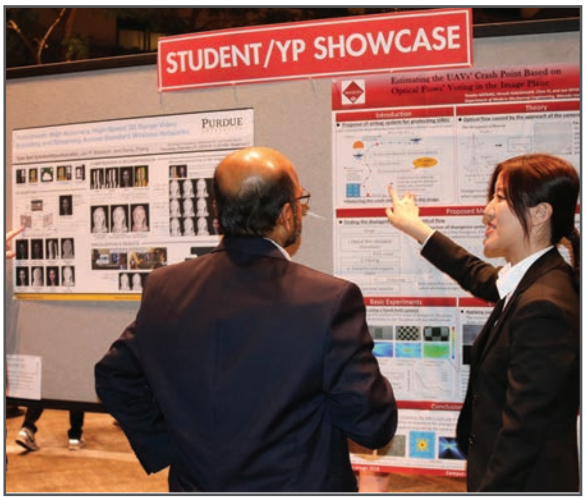
JOIN US AT THE NEXT EI!

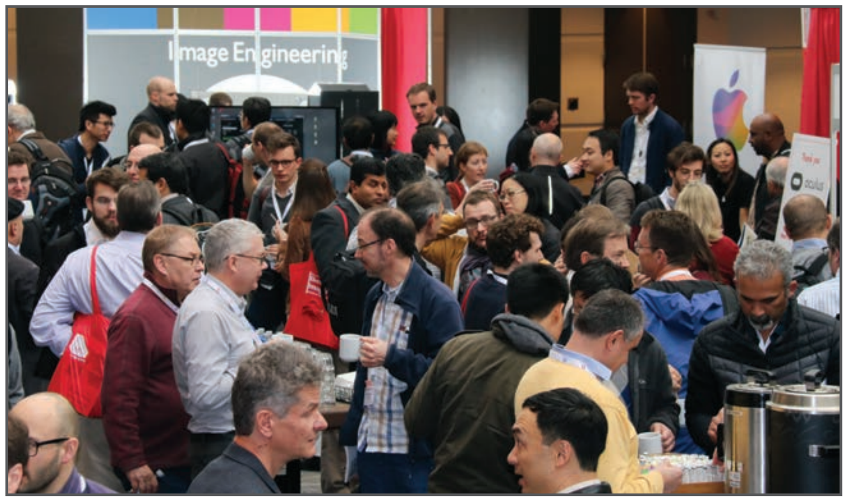
IS&T International Symposium on

Electronic Imaging

SCIENCE AND TECHNOLOGY

Imaging across applications . . . Where industry and academia meet!





• SHORT COURSES • EXHIBITS • DEMONSTRATION SESSION • PLENARY TALKS •
• INTERACTIVE PAPER SESSION • SPECIAL EVENTS • TECHNICAL SESSIONS •

www.electronicimaging.org

IS&T
imaging.org