1st International round robin on EL imaging: automated camera calibration and image normalisation

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ABSTRACT: Results from the first international Round Robin on electroluminescence (EL) imaging of PV devices are presented. 17 Laboratories across Europe, Asia and the US measured EL images of ten commercially available modules and five single-cell modules. This work presents a novel automated camera calibration and image scaling routine. Its performance is quantified through comparing intensity deviation of corrected images and their cell average. While manual calibration includes additional measurement of lens distortion and flat field, the automated calibration extracts camera calibration parameters (here: lens distortion, and vignetting) exclusively from EL images. Although it is shown that the presented automated calibration outperforms the manual one, the method proposed in this work uses both manual and automated calibration. 501 images from 24 cameras are corrected. Intensity deviation of cell averages of every measured device decreased from 10.3 % (results submitted by contributing labs) to 2.8 % (proposed method). For three images the image correction produced insufficient results and vignetting correction failed for one camera, known of having a non-linear camera sensor. Surprisingly, largest image quality improvements are achieved by spatially precise image alignment of the same device and not by correcting for vignetting and lens distortion. This is due to overall small lens distortion and the circumstance that, although vignetting caused intensity reduction of more than 50%, PV devices are generally positioned in the image centre in which vignetting distortion is lowest.

Keywords: Electroluminescence, Evaluation, PV module, Software

1 FIRST INTERNATIONAL ROUND ROBIN ON EL IMAGING

Electroluminescence (EL) imaging is a fast and non-destructive method for spatial characterisation of photovoltaic (PV) cells and modules [1]. An international inter-lab comparison (Round Robin) was conducted to further harmonise EL imaging methods, to estimate its potential for quantitative analysis and to qualify the respective IEC TS 60904-13:2018, which was at the time a draft standard [2].

17 laboratories across the EU, USA and Asia took part at this first Round Robin (RR). The experiments were conducted between January 2016 and September 2017. An initial evaluation on image quality of the RR data set was presented in [3]. This second work compares results, obtained from two different camera calibration methods, with results submitted by the contributing laboratories.

In this section an overview of the RR is given. Section 2 and 3 present two different methods (manual vs automated) for vignetting and lens calibration. Finally, EL intensity deviation of the RR data set is presented in Section 4.

Five single-cell-mini modules (short ‘cells’) and 10 commercially available modules are measured (Fig. 1). EL images are captured at two given currents corresponding to 10% and 100% of the devices nominal short circuit current ($I_{sc}$). Additionally, calibration images to correct for vignetting and lens distortion are taken (manual calibration, Fig. 5a).

Some laboratories submitted results for multiple camera or imaging setups. This resulted in 24 laboratory-camera combinations (short ‘camera’). For the sake of anonymity, these sets are assigned single letters for CCD and CMOS cameras sensors (A-U) and double letters, starting with ‘X’ for InGaAs camera sensors (XA-XC).

![Figure 1: PV devices measured at the Round Robin](image)

Two types of intensity deviation ($E_{l,i}$ and $E_{A,i}$, Fig. 2) are evaluated in this work: Intensity deviation of corrected EL images ($I_{i}$) and their cell averages ($A_{i}$). For both, the root mean square (RMS) difference between all images or cell averages (placeholder: #) and their temporal average is calculated. The temporal average ($\text{mean}_{t}$) is defined as element-wise average of multiple images.

$$E_{#} = \sqrt{\text{mean}_{x,y}(\# - \text{mean}_{t}(\#))^2} \text{ [%]}$$  (1)
For both parameters, $I_i$ is divided by its bit depth (255, for 8-bit images) and the border of 50 pixels around the device is removed.

![Scheme for calculating the intensity deviation from cell averages](image)

**Figure 2:** Scheme for calculating the intensity deviation from cell averages ($E_{A_i}$) of corrected EL images (only 3 shown for clarity)

Nine measurement protocols from eight labs containing a quantitative analysis of the taken images are submitted. An elementary part of quantitative analysis is the measurement of cell averages of the EL intensity. Seven labs stated that their cell averages are obtained fully automated. However, a direct comparison of the intensity deviation of submitted cell averages ($E_{A_k}$) of Mod1-10 (Fig. 3) reveals a median over 15% (Fig. 4b). If the cell intensities are chosen randomly in a uniform distribution from 0 to 100%, the deviation would be only twice the size (Fig. 4a).

The measurement plan specified to scale intensities between 0% (darkest cell) and 100% (brightest cell). However, in Fig. 3 cell averages of camera F and K do not contain a 0% or 100% cell. The $E_{A_k}$ can be reduced to 10% (Fig. 4c) if all cell averages ($A_i$) of every module are normalized as follows:

$$A_i = \frac{A_i - \min(A_i)}{\max(A_i) - \min(A_i)}$$

In this work, intensity deviation of EL images of the same device and imaged by different cameras is reduced to 2.8% (Fig. 4d). For this, a method for image scaling and two methods for removal of lens distortion and vignetting are presented. It is stated that EL signal deviation due to different device temperatures, instabilities and cracks, introduced during transport between the labs, are not analysed. However, the value obtained in this work is close to the EL signal uncertainty of 2.8%, estimated in [3].

Camera calibration and image correction are extensively discussed in [3]. In contrast to this, this paper focusses on a novel automated calibration method to extract vignetting and lens distortion from EL images directly. It therefore does not rely on additional images taken (Fig. 5b). Also, a method for image intensity scaling is introduced.

Sensor nonlinearities and spatial variations of pixel sensitivity (especially for InGaAs cameras) can heavily reduce the calibration quality. Their calibration and correction are not investigated in this work. All vignetting maps, lens calibrations and corrected images analysed in this work can be found at [4].

**2 VIGNETTING MEASUREMENT**

Vignetting describes the gradual intensity reduction from the image centre to its corners. The vignetting map ($I_v$) is scaled 0 to 1 and is of the same size as an EL image ($I_{EL}$). For linear camera sensors, vignetting correction is done by element-wise division $I_{EL} / I_v$. The effective vignetting map is specific for the camera system used [5]. Its dependency on wavelength, exposure time and aperture are not analysed in this work.

2.1 Manual calibration

All laboratories were asked to submit at least ten illuminated and five dark (background) images, taken with the same imaging setup. To illuminate the camera sensor homogeneously, a mobile phone or tablet displaying a red screen is placed on top of the camera lens at different positions. It is referred as method A in [5]. Using a red screen is originally proposed in [6]. The later publication [5] however discouraged its use due to vignetting overcorrection from using a red-, instead of a near infrared (NIR) light source.

For 22 cameras vignetting images are submitted, while two are missing. Background images, needed for vignetting measurement, are not available for four cameras. For those cases, the background level is set to the maximum position of the first peak of the intensity histogram from one of the background images of the submitted EL image data of that camera.

2.2 Automated calibration

The main challenge for vignetting calibration is the necessity for a homogenous light source to illuminate the camera sensor. The methods discussed in [5] attempt to eliminate this inhomogeneity by spatial or temporal averages. However, all methods rely on additional calibration images. In this work, $I_v$ is extracted from EL images through a mixed spatial and temporal average of all EL images taken at 100% $I_{EC}$. For cameras measuring...
both modules and cells, 15 images are taken. For cameras measuring only cells, only five images are available. For a sufficient quality, the author recommends using at least 30 images. The algorithm to extract vignetting from EL images is as follows (Fig. 6):

1. Subtract background images, if available, or remove estimated background level from EL images.
2. Mask background areas through applying a threshold condition, such as Otsus method [7]. Average unmasked areas with a spatial mean filter. Here, a kernel size of 10% of the image width is used.
3. Divide every averaged image by its maximum and apply a temporal average on all images, excluding background areas.
4. To smoothen the result and to remove empty areas a polynomial filter, the radial average and the Kang-Weiss function are applied independently [5]. The output resulting in the respective lowest RMS difference to the temporal average is chosen as calibration map ($I_{cal}$).

The differences between manual and automated vignetting measurement are summarized in Table 1.

Automated vignetting calibration strongly depends on the quality and quantity of the available EL images. As Fig. 7 shows, automated calibration can fail when the temporal average is not capable of averaging out the devices spatial inhomogeneity and/or not a sufficiently large area is covered.

Table 1: Differences between automated and manual vignetting measurement methods

<table>
<thead>
<tr>
<th>Camera</th>
<th>Automated Calibration</th>
<th>Temporal Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>a)</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>b)</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7: a) Temporal average and derived fit of automated calibration for camera S and E; Strong differences to manual calibration (b) indicate failure of automated calibration

2.3 Vignetting quality

The improvement due to vignetting correction ($Q_V$), Fig. 8 is quantified through comparing the straightness of an image ($q_V(I)$) before ($I_{EL}$) and after vignetting correction ($I_{cal}$):

$$Q_V = 1 - \frac{q_V(I_{EL})}{q_V(I_{cal})} \%$$

The image straightness is defined as the standard deviation ($\sigma$) of a line wise horizontal and vertical image average ($A_x, A_y$):

$$q_V(I) = \sigma(A_x(I)) + \sigma(A_y(I))$$

Background areas are excluded from $A_x$ and $A_y$ using a threshold condition, such as Otsus method.

It is stated, that $Q_V$ depends on the homogeneity of the imaged PV devices and that a high $Q_V$ is not a guaranty for high calibration quality since the undistorted source image is unknown. For robust quality metrics, refer to [5].

The $Q_V$ distribution of the Round Robin data set is shown in Fig. 9a. Next to it, Fig. 9b displays the average of the individual $I_{cal}$ maps. Since $I_{cal}$ is bound between 0 and 1, an average of 1 (100%) corresponds to zero distortion from vignetting. It can be seen, that manual calibration tends to have a lower average vignetting and with it a higher extend of vignetting distortion. As [5] discusses, vignetting can depend on the waveband of the light source used to measure it. It was found that visible red light causes a more pronounced vignetting and therefore a vignetting overcorrection in comparison to NIR.

Fig. 9 allows the suggestion that for the Round Robin data set automated vignetting calibration generates slightly more homogenous vignetting maps at a higher quality.

Figure 6: Algorithm to estimate vignetting of one camera from multiple EL images of different PV modules

Figure 8: Example vignetting map (a), uncorrected- (b) and vignetting corrected image (c): $A_x$ and $A_y$ displayed as green and blue lines; $Q_V = 78.7\%$

Figure 9: Comparison of vignetting quality parameters
3 LENS DISTORTION

3.1 Grid detection

To estimate image lens distortion, reference points are detected. In case of manual calibration, checkerboard patterns (Fig. 5a) are imaged and the corner points of the black squares are detected using the C++ library OpenCV [8], [9]. For the automated calibration the following steps are applied:
1. Detect the corners of a bright quadrilateral object (here: PV device) in the image.
2. Estimate the number of cells and busbars from the horizontal and vertical image average along the detected device edges.
3. Refine positions of all detected lines using a maximum likelihood approach.

Example algorithms for step 1 and 3 are provided by the main author in [3]. Another routine, incorporating machine learning, is detailed in [10].

The quality of the resulting cell grid lines is inspected visually using the image material from the RR. In this work, grids build by PV devices are mostly detected correct (Fig. 10a). Images with low signal-to-noise ratio and images displaying only part of the PV device cause erroneous results. Also, the number of cells of the thin-film modules Mod9-10 is mostly detected wrong. The intensity reduction of their cells is often inferior to the intensity deviation from intrinsic and extrinsic defects and therefore hard to detect using machine vision (Fig. 10c,d).

![Image 10: Successful (a) and faulty (b,d) grid detection; c: Cells of thin film modules are often hard to differentiate](image)

The qualitative success rate is listed in Table 2. Devices with visually correct results are counted as 1 (Fig. 10a). Devices with incorrect results are counted as 0. Device position, number and position of cells as well as number and position of busbars are evaluated separately.

Table 2 shows, that the device position is detected correctly in 98% of all cases. Number of cells and busbars are detected correctly in 85% of all cases.

<table>
<thead>
<tr>
<th>Device position</th>
<th>n. cells</th>
<th>n. busbars</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>98.4</td>
<td>84.6</td>
</tr>
<tr>
<td>1 Only SNR&gt;5</td>
<td>98.7</td>
<td>86.5</td>
</tr>
<tr>
<td>2 Fully imaged</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 [2] only</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>4 [2] only modules</td>
<td>98.1</td>
<td>79.6</td>
</tr>
<tr>
<td>5 [2] only thin film</td>
<td>93.1</td>
<td>6.9</td>
</tr>
<tr>
<td>6 [2] only InGaAs</td>
<td>94.6</td>
<td>81.1</td>
</tr>
</tbody>
</table>

3.2 Lens calibration

For both manual and automated calibration, the camera intrinsics and distortion parameters are calculated using the OpenCV function `calibrateCamera`. Amongst the available standard, rational and thin prism lens model, the model resulting in the lowest reprojection error (usually the standard model) is chosen for every calibration individually. The differences between manual and automated calibration are summarized in Table 3.

<table>
<thead>
<tr>
<th>Input</th>
<th>Manual</th>
<th>Automated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Images of a checkerboard pattern</td>
<td>EL images of PV modules</td>
<td></td>
</tr>
<tr>
<td>Waveband</td>
<td>Mostly visible</td>
<td>Near infrared (EL)</td>
</tr>
<tr>
<td>Distance</td>
<td>Mostly in image plane</td>
<td>Image plane (EL)</td>
</tr>
<tr>
<td>Evaluated area</td>
<td>Limited to checkerboard-pattern positions</td>
<td>Limited to PV-module positions</td>
</tr>
</tbody>
</table>

Table 3: Differences between both evaluated lens calibration methods

- **Factors limiting calibration quality**
  - Number of available EL images of PV modules
  - EL image quality (sharpeness and noise)
  - Quality of grid detection and precision of edge-alignment algorithm

3.3 Lens calibration quality

To assess the lens calibration quality, four quality numbers are applied to the RR data set: a) detected corner points, b) deflection assessment, c) relative improvement of the line accuracy, and d) point uniformity.

a) Detected corner points. For every camera, an average of 19 images of a checkerboard pattern at different positions within the image are submitted. The provided checkerboard pattern contains 8x6 corners. This results in an average of around ~900 corner points available for every manual calibration (Fig. 11a).

![Figure 11](image)
For the automated calibration, only the crystalline modules Mod1-Mod8 can be used for calibration since the one-cell mini modules and thin-film modules do not provide the minimum number of 4 corner points in x and y dimension.

Only EL images at 100% I_ssc are used for calibration since these images have a significantly higher image quality. Also, the images devices are generally not moved for 100% and 10% I_ssc images. With eight available module images and detected grids of 5x9 to 7x13 (dependent on number of cells in the module), an average of ~550 corner points (n_k) is available per camera.

b) Deflection assessment. In this work, deflection describes the spatial shift due to correction from lens distortion. Both automated and manual calibration lead to similar results for average and maximal deflection (Fig. 11b). With 0.5% relative to image width, average deflection is so small, that lens distortion is hardly visible. However, if two images from different cameras are compared, the distance between features can be up to 50 px (given an image width of 5000 px and an opposing deflection of 0.5%).

c) Relative improvement of the line accuracy. The relative improvement (Q_L), relates the straightness of gridlines (G), before (G_D) and after correction from lens distortion (G_L). The straightness (q_L(G)) is defined as average of all vector magnitudes, build by the difference of an ideal straight gridline (G_ideal) to the given (G).

\[
Q_L = 1 - \text{mean}(q_L(G_{L}))/q_L(G_{D})[\%] \\
q_L(G) = \text{mean}(|G - G_{\text{ideal}}|)
\]

As Fig. 11c shows, relative improvement is in most cases positive although the result varies strongly from 5% to almost 80%. Improvement is roughly 8% higher for manual calibration. This is reasonable since the detection of black corners on a white background should have a higher precision than the detection of cell corners in an EL image.

d) Point uniformity: For high quality lens calibration, corner points should be distributed across the whole image [11]. Fig. 12 compares two extreme cases. In Fig. 12a the chosen checkerboard pattern is too small or far away and only moved within a small area. In Fig. 12b corner points detected from Mod1-Mod8 in the EL images are widely distributed. The uniformity of the corner point distribution (U_L) is determined as follows:

1. Split the imaged area in 10x10 cells.
2. Count number of corner points within each cell.
3. Divide all cells by the highest value in the grid to obtain the discrete point density (\rho_{10x10})
4. Define point uniformity (U_L) as average of \rho_{10x10}:

\[
U_L = \text{mean}(\rho_{10x10})
\]

A point uniformity of 100% corresponds to a fully homogenous distribution of corner points in an image. Surprisingly, point uniformity of the automated calibration is twice that of the one obtained from manual calibration (Fig. 11d). When using the checkerboard pattern in the same plane as the PV module then PV modules occupy a larger area in the image.

Therefore, the point uniformity extracted from the EL image of the PV module is higher. Additionally, less care might have been given to the additionally imaged checkerboard patterns, since only one of eight laboratories was stated in their submitted protocol to execute calibration and correction from lens distortion as part of their EL imaging routine.

For the Round Robin data set it is found (Fig. 18) that the quality indicator (Q_L2) based on corner point number (n_k) and -uniformity (U_L) is more reliable than Q_L1:

\[
Q_{L2} = U_L \cdot n_k
\]

4 IMAGE COMPARISON

To compare the ability of manual and automated calibration to reduce camera dependent distortion, 15 EL images were at 100% and 10% I_ssc from all 24 cameras are corrected according to the following procedure (Fig. 13). A complete image set includes two consecutively captured EL images and two background images.

The EL image correction procedure contains the following steps:

1. Removal of image artefacts
   - Single-time-effects: Both taken EL images are averaged. If the image difference exceeds a given threshold, the corresponding minimum is used instead [3].
   - Hot pixels: All image areas where the ratio image vs. median filtered image exceeds a threshold are set to the median filtered result [3].
2. The background image is (after step 1) subtracted from
the EL image.

3. The corrected EL image \( (I_{nu}) \) is divided by the vignetting map \( (\nu) \).

4. Lens distortion is removed (Section 3.2).

5. For two cameras, larger modules are only available as part images (Fig. 14a). These images are stitched together in two steps:
   - Estimate the position of a part image in the stitched image (depending on size of overlap either through key-point- or template matching).
   - Average all part-images after perspective warp using ‘blurry rectangles’ as weights (Fig. 14c).

![Image 14: Image stitching steps](image)

6. All images, taken by camera M, are set as template images due to their sufficient quality and no missing images. Perspective distortion is obtained from the result of grid detection (Section 3).

7. For all other cameras, perspective distortion is obtained through matching features between a template image (e.g. Mod3 from camera M and Mod3 from camera P). From the different positions of matched features, a single perspective transformation (homography) matrix is calculated.

   Perspective correction using a single homography matrix is not suitable to perfectly align images, especially if lens distortion remains, the images are of low quality (and only few features match) or the imaged devices are slightly bent. A precise alignment algorithm, similar to the one presented in [3] is used to reduce remaining distortion (only case ‘bestPrecise’).

8. To equalize the image intensity spectrum a cumulative distribution function (CDF) of the image intensity is calculated. The intensities at the left end of the CDF (1 and 2%) and the right end (98 and 99%) are calculated (Fig. 15). The intensity difference between 1 and 2% respective 98 and 99% is subtracted (left) or added (right) to obtain the representative intensity range.

![Image 15: Scheme to obtain the representative intensity range from evaluating the CDF at 1, 2, 98 and 99%](image)

9. If the image is not a template \( (I_j) \) the representative intensity range \( (I_{min}, I_{max}) \) is determined from a linear fit \( (y = mx + n) \) of the images CDF to the templates CDF (Fig. 16):

\[
I_{min} = \frac{I_{max} - n_m}{m}, \quad I_{max} = \frac{I_{max} - n_m}{m}
\]

\[
m, n \rightarrow \text{argmin} \left( \text{abs}(\text{CDF}(I_j) - \text{CDF}(I_{ref} \cdot m + n)) \right)
\]

Powell’s method [12] is used to solve Eq. 10.

![Figure 16: Mod7 at 100% \( I_{ref} \), imaged by cameras M, C and Q; template image is M; a) images at original intensity range; b) images at representative intensity range; c) CDF before fit; d) CDF after fit using Eq. 10](image)

Figure 16: Mod7 at 100% \( I_{ref} \), imaged by cameras M, C and Q; template image is M; a) images at original intensity range; b) images at representative intensity range; c) CDF before fit; d) CDF after fit using Eq. 10.

Image similarity is compared for the following cases:
- **base** – Image correction according to Fig. 13, but without vignetting removal [step 3] and lens correction [step 4].
- **manual** – Vignetting removal and lens correction using only manual calibration (if available, else no correction).
- **automated** – Vignetting removal and lens correction using only automated calibration (if available, else no correction).
- **best** – Vignetting removal and lens correction using either manual or automated calibration, dependent on the highest relative improvement \( Q_r, Q_{LM} \) (Eq. 3, 8).
- **bestPrecise** – same as case best using ‘precise alignment’ [step 7].
- +100% \( I_{nu} \) – same as case bestPrecise but using only high current EL images to allow direct comparison to cell averages, submitted by the Round Robin contributors.

Fig. 17 displays the intensity deviation of all corrected EL images \( (E_I) \) and their cell averages \( (E_A) \) of all compared cases. Both boxplots follow a similar trend. Surprisingly, both \( E_I \) and \( E_A \) increase significantly for manual calibration. Possible reasons are already discussed in Section 2.3 and 3.3.

For both parameters, automated calibration outperformed case base and case manual. This indicates, that a calibration using only EL images can result in higher quality EL image correction in comparison to no or manual calibration. Case best, which uses either manual or automated calibration, outperforms case automated.

The additional precise alignment of case bestPrecise causes the largest decrease for \( E_I \), did however not influence \( E_A \) since image intensities remained mainly unchanged and only deflection changed slightly.
The individual influence of both vignetting and lens distortion correction is visualized in Fig. 18. It contains an additional case best2. For vignetting, this case chooses either manual or automated calibration depending on the respective higher average vignetting (Fig. 9b).

For lens distortion, the initial relative improvement $Q_L$ is used as selection criterion. For cell averages the positive effect of lens calibration can be neglected (Fig. 18b). However, the relative improvement, based on the distribution of detected corner points ($Q_{L2}$) used in case ‘best’ is favourable to $Q_L$ which only considers the grid straightness. For vignetting calibration no difference between case ‘best’ and ‘best2’ is visible. This allows the conclusion that statistically more homogenous vignetting maps also generate better image corrections. Again, it must be emphasized that the vignetting calibration method used in the Round Robin is found to cause vignetting overcorrection and is not encouraged any more [5].

The following figures are an excerpt of [4]. In most cases, images corrected in case bestPrecise are visually more similar than the ones of case base (Fig. 19).

Some EL image differences display variable EL signal either due to instabilities (Fig. 20 left) or due to introduction of extrinsic defects (cracks) during the course of the Round Robin (Fig. 20 right).

Corrected EL images from camera P are the only ones that clearly show effects of a non-linear camera sensor. This nonlinearity causes amplified low image intensities and suppressed higher intensities. This can be seen through a more pronounced vignetting for low current (darker) EL images in comparison to high current images (Fig. 21 left vs right). Since both images are corrected with the same vignetting map, remaining vignetting can be found in the low current image and vignetting overcorrection is visible for the high current image.

It is stated that only K and P are consumers product cameras with a CMOS sensor. All other cameras are based on a silicon CCD or InGaAs sensor.

Amo

Amongst all images in case bestPrecise, the image processing algorithm (Fig. 13) failed three times exclusively on low current (and often low quality) 10% $I_{SC}$ images:
- camera K, R (Cell1): wrong device rotation
- camera A (Mod5): failed image stitching
5 CONCLUSION

This paper presents and validates a novel automated camera calibration method which does not depend on additional calibration images. In comparison to manual calibration it allowed for more accurate image correction. Even higher accuracy is reached when, dependent on presented quality parameters, either the manual or the automated calibration is chosen.

This work further presents methods to scale image intensities and to measure intensity similarity. For all 501 processed image sets, the proposed image correction case bestPrecise failed on three images. Vignetting correction produced insufficient results for only one camera, known to have a non-linear camera sensor. Non-linearity correction will be covered in future work.

The comparison of intensity deviation shows that contrary to prior assumptions, the largest EL quality improvement comes from precise spatial alignment of images to be compared, followed by vignetting correction. Especially for cell averages, the positive effect of lens calibration is negligible. For 100% I_{EC} case bestPrecise resulted in a three times lower intensity deviation of cell averages (2.8%) than the one generated from data submitted by the Round Robin contributors (10.3%, Fig. 4).

All key features that enable quantitative EL imaging are included in QELA, a freely accessible software for EL image analysis [13]. It uses the automated calibration for its integral image correction routine. It is planned to enable submission of own manually taken camera calibrations which will only be applied if the quality metrics presented in this work indicate a higher quality.

7 REFERENCES