

PROGRESS ON DISTRIBUTED IMAGE ANALYSIS FROM DIGITAL CAMERAS AT ELSA USING THE RABBITMQ MESSAGE BROKER

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Abstract

In the course of modernization of camera based imaging and image analysis for accelerator hardware and beam control at the ELSA facility, a distributed image processing approach was implemented, called FGrabbit. We utilize the RabbitMQ message broker to share the high data throughput from image acquisition, processing, analysis (e.g. profile fit), display and storage between different work stations to achieve an optimum efficacy of the involved hardware. Re-calibration of already deployed beam profile monitors using machine vision algorithms allow us to perform qualitative beam photometry measurements to obtain beam sizes and dynamics with good precision. We describe the robustness of the calibration, image acquisition and processing and present the architecture and applications, such as the programming- and web-interface for machine operators and developers.

INTRODUCTION

The ELSA facility [1] deploys around 50 optical beam monitors based on luminescence screens (Chromox or OTR) and synchrotron radiation. The previous installation of cameras with analogue video signal output provided mediocre beam analysis capability due to limited signal quality and the lack of comprehensive camera control. To obtain qualitative beam data from photometry we modernize hardware and software of the optical monitors, primarily utilizing Ethernet-capable digital cameras controlled with non-commercial camera drivers and open source machine vision libraries for image calibration. The FGrabbit framework was created [2] to provide resource-optimized camera control, data handling and computing power based on the RabbitMQ message broker for distributed analysis. A Gigabit Ethernet (GigE) network between PoE-capable switches links processing computers and image generating devices, such as GenIcam [3] compatible digital cameras, other digitizers or image generating programs. A graphical user interface allows access to the FGrabbit framework from the accelerator control system or the facility website and provides comprehensive device and image control.

ARCHITECTURE

The architecture of the FGrabbit framework is depicted in Fig. 1. All peripheral devices (cameras, computers) participating in the FGrabbit framework communicate through a GigE network, separated from the ELSA control system, but accessible through a gateway computer. As camera control and readout can be achieved through various

drivers. We favor the Aravis [4] driver in combination with GenICam [3] compatible digital cameras. Streams from other drivers (e.g. Video4linux¹), VNC² servers or image generating programs may also be used as input for the FGrabbit framework. Comprehensive image calibration can be applied via the OpenCV computer vision library [5] to account for beam profile distortions resulting from tilted screens (extrinsic properties) or lens imperfections of the imaging system (intrinsic properties). Calibrated images are typically cropped to a useful area of interest (AOI) and ideally visualize an undistorted transverse cross section of an observed beam with correct pixel to millimeter scaling. The calibrated images are typically reduced in size, allowing to economically stream images from multiple cameras through the GigE network. The data load from imaging and image analysis is handled by the RabbitMQ message broker. Computing power (e.g. for computational expensive 2D profile fits) is distributed to multiple standard computers within the network. A QT-based [6] graphical user interface

¹ <https://www.kernel.org/doc/html/v4.8/media/v4l-drivers/>

² virtual network computing

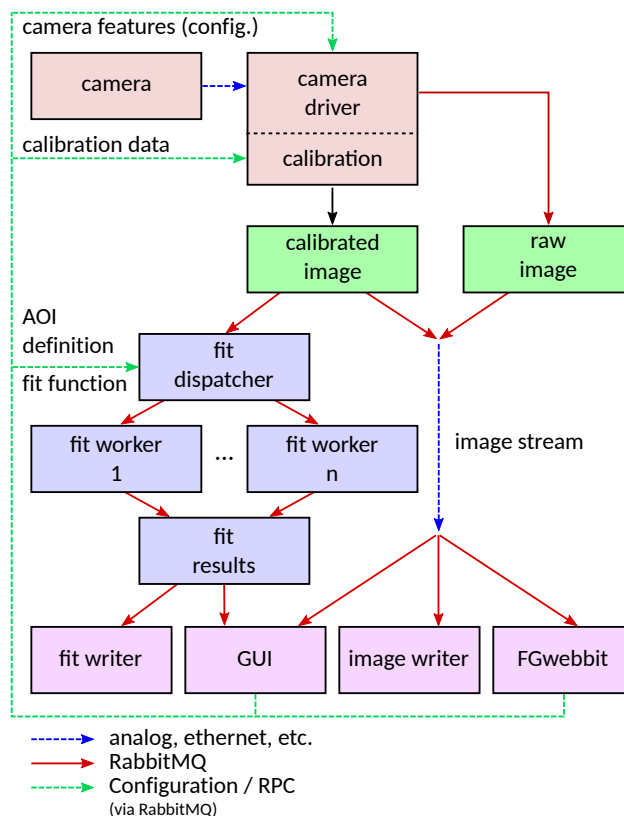


Figure 1: Architecture of the FGrabbit framework.

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(GUI) allows full-scale user interaction. A web interface allows down-scaled interaction from anywhere via the ELSA website³.

Performance

A RabbitMQ message is limited to 128 MB, defining the limit for the streamable image size. While the cumulative streaming data rate is limited by the network bandwidth, the computationally expensive fit calculations are outsourced to an arbitrary amount of computers participating in the net- and framework. Computation and network load is conveniently monitored via the RabbitMQ analysis interface. Using standard desktop computers we achieve repetition rates up to 10 Hz of display and beam analysis on a sufficiently large AOI (2D data fit on a hundreds by hundreds large pixel grid).

MEASUREMENT PRECISION

Image Calibration

Beam images taken from e.g. Chromox screens suffer from projection and optical imaging errors which can be classified as intrinsic and extrinsic properties⁴. To obtain a projection-free image without optical errors, a 3×3 projection matrix P can be applied to the uncalibrated image

$$P = K \cdot M, \quad M = H \cdot \vec{t}, \quad (1)$$

where K denotes to the intrinsic and M to the extrinsic properties of the individual setup. M is calculated from a rotation matrix H and a translation vector \vec{t} . The main influence to the extrinsic uncertainties are image distortions due to the observation perspective, e.g. a screen under a tilt angle of typically 45° . This can be resolved by using a homography matrix as rotation matrix. The matrix entries can be computed from an image taken with a regular pattern of known dimensions (checkerboard or circular patterns consisting of $m \times n$ corners or circles, respectively). Such a calibration image can be temporally installed on the surface of a screen, as demonstrated in Fig. 2. A calibration pattern printed on cardboard with a regular laser printer usually suffices the required image quality. For the calibration we use an OpenCV [5] approach as depicted in Fig. 3. Therewith, a raw image is captured on which an OpenCV detector function finds the position of the corners of the checkerboard (or centers of circles, resp., compare with circular calibration patterns in Appendix). The obtained coordinates are then optimized by performing an additional search for the position using sub-pixel accuracy. Then a coordinate grid that matches the shape of the used pattern is created with a predefined step range. By mapping the found image coordinates into the real world grid the homography matrix can be calculated.

Measurement Error

The radial displacement of the transformed positions to the expected grid is classified as the calibration error. To

³ <https://www-elsa.physik.uni-bonn.de>

⁴ compare e.g. with <https://docs.opencv.org/4.x/>

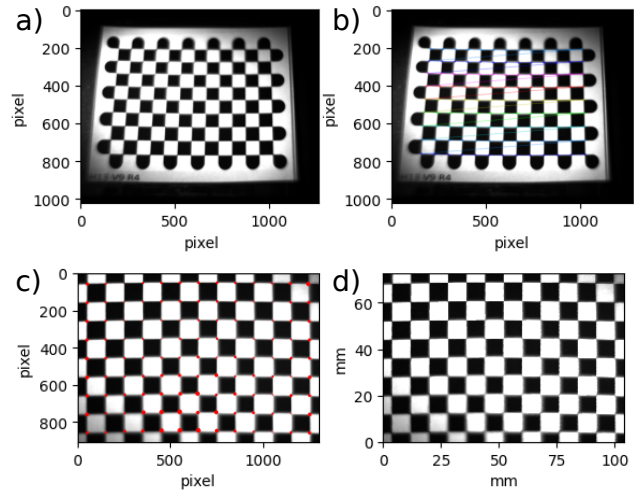


Figure 2: Image calibration using a printed checkerboard pattern on a tilted screen and OpenCV [5] transformation functions: a) original image, b) recognized pattern, c) image after homography transformation including precision errors (red circles), d) scaled and calibrated image.

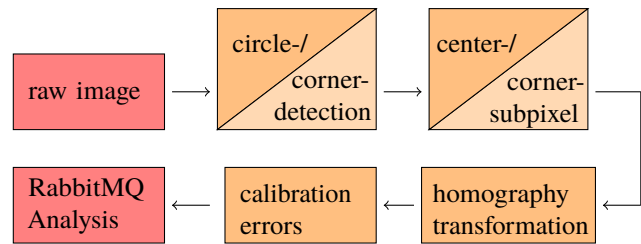


Figure 3: Schematic sketch of the calibration chain. The chain is divided into RabbitMQ framework (red) and OpenCV tasks (orange). The chain can be applied to circular patterns (dark-orange) and checkerboard patterns (light-orange).

minimize statistical fluctuations a sequence of n images is recorded to obtain an averaged radial error, as visualized in Fig. 2 c). Intrinsic properties, such as radial or tangential distortions introduced by the camera lens may be represented by

$$\begin{aligned} x_{\text{dist,rad}} &= x(1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \\ y_{\text{dist,rad}} &= y(1 + k_1 r^2 + k_2 r^4 + k_3 r^6) \\ x_{\text{dist,tan}} &= x + (2p_1 xz + p_2(r^2 + 2x^2)) \\ y_{\text{dist,tan}} &= y + (p_1(r^2 + 2y^2) + 2p_2 xy) \end{aligned}$$

with distortion coefficients $(k_1, k_2, k_3, p_1, p_2)$. OpenCV functions allow to determine these coefficients and to undistort the respective image. The distortion coefficients are obtained from taking multiple pictures of a regular pattern from multiple angles⁵. We find that intrinsic distortions play a neglectable role with usage of industry standard photographic objectives (e.g. $f = 16$ mm) for our monitor setups.

⁵ For details see https://docs.opencv.org/4.x/dc/dbb/tutorial_py_calibration.html

The calibration error determined from the deviation from the keypoint grid can be interpolated to every pixel, for example using radial basis functions⁶, as shown in Fig. 4. Thereon, non-linear weighted fit algorithms can be applied to take local uncertainties into account. For this purpose the GNU scientific library (GSL) [7] back-end of the in-house developed fit library is used. For the unweighted case the common function to be minimized is

$$\Phi(x) = \frac{1}{2} \|f(x)\|^2 = \frac{1}{2} \sum_{i=1}^n f_i(x_1, \dots, x_p)^2,$$

where f is the residual function, n the number of data points (e.g. the number of pixels of the captured image) and p is the number of parameters or the dimension of the fit function. In the weighted case this formula is expanded to

$$\Phi(x) = \frac{1}{2} \sum_{i=1}^n w_i \cdot f_i(x_1, \dots, x_p)^2, \quad (2)$$

where an individual weight w_i is added for each individual data point. These weights can be utilized for various purposes or represent different effects. Using the obtained inverse calibration variances as weights allows us to suppress potential errors introduced by the calibration process. Furthermore, this allows to mask areas on the screens that exhibit altered behavior to achieve a better fit result. In Fig. 4 a profile captured on a calibrated screen as well as the weighted fit to this data is shown. The inverse variance of the calibration was used as weight, resulting in a profile parameter deviation of up to 2% comparing weighted and unweighted case.

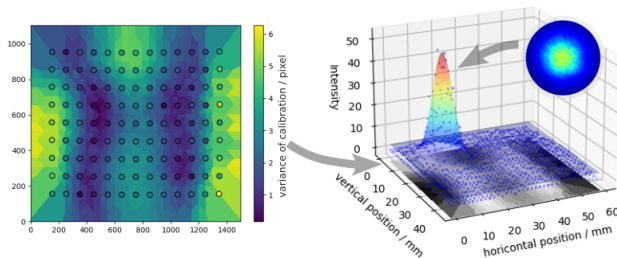


Figure 4: The variance of an exemplary screen calibration with circled nodes and in-between interpolation (left) and a beam profile image on a calibrated screen analyzed with a weighted fit algorithm (right).

FGRABBIT INTERFACES

While RPC⁷ commands allow for automated settings and application of the FGrabbit framework, the graphical user interfaces provide practical user interaction and monitoring capability.

Operator GUI

A QT-based [6] graphical user interface allows for convenient control of camera and imaging settings (Fig. 5). The

⁶ e.g. using Python SciPy RBFInterpolator

⁷ remote procedure call

numerous available camera settings are listed and manipulatable, as shown in Fig. 6. Favorite settings can be marked and made available for the main menu. A detail view of the image analysis gives the operator fast and comprehensive feedback of fit parameters and fit quality.

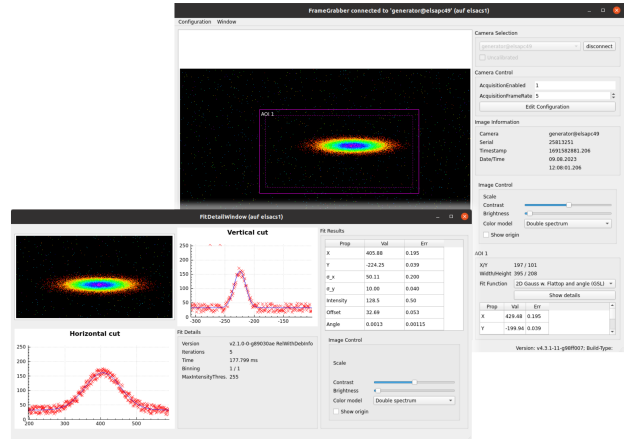


Figure 5: FGrabbit graphical user interface with detail view on profile analysis.

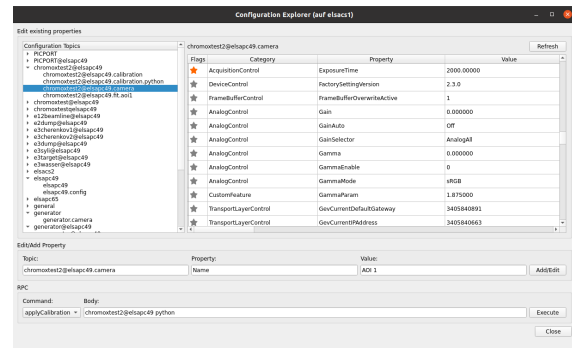


Figure 6: FGrabbit configuration explorer listing all properties of the digital cameras obtained by the Aravis [4] driver.

FGwebbit

In addition to the Operator GUI a slimmed down Interface is accessible via an in-house developed web application, called FGwebbit. It provides platform independent access to FGrabbit combined with flexible availability via internet and intranet. The responsive architecture (Fig. 7) enables control and views optimized for handheld devices when working on experiments or maintenance tasks in confined spaces. The simplified user interface provides access to live views of multiple camera streams simultaneously. The user interface is complemented by a modular card for each camera. Within a camera card, favorite settings of the attached device are directly available. An expert menu contains all available device parameters for detailed adjustments, accompanied by tooltips for the available settings. Each client can adjust the compression, frame rate, color model and preference for calibrated or uncalibrated data. These settings are saved

and applied only for that particular client, allowing for an optimized application e.g. for mobile use with limited data availability. The web application is prepared to host a global overview of the state of the FGrabbit systems, summarizing the status of all associated nodes and devices. Furthermore, the application provides space for the documentation of the FGrabbit framework and interfaces.

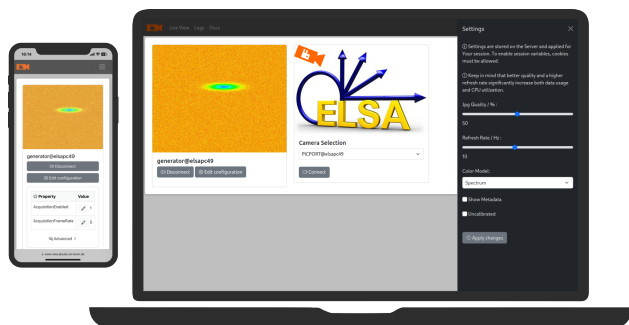


Figure 7: Responsive behavior of the FGwebbit interface and active session settings menu.

The FGwebbit backend extends the FGrabbit Python interface [2] and uses the lightweight Python web framework Flask. To reduce network traffic and data usage in mobile or low bandwidth environments, the live camera feeds are served as compressed JPEG streams. The OpenCV library [5] is used for compression and color model application. Further streamlining is achieved by smart handling of TCP connections to the underlying FGrabbit framework. Multiple clients and simultaneous streams from or to the same camera device are detected and clustered into a single open TCP connection. This alone significantly improves connection times for additional clients and reduces server load. Unused TCP connections are closed after a predefined timeout, freeing up system resources. For modern design and easy responsive implementation the popular Bootstrap frontend toolkit is used, resulting in familiar design elements and usability concepts for FGwebbit.

CONCLUSION

Screen calibration for extrinsic properties is the key advantage for beam photometry with monitors installed in environments typical for accelerator beamlines. Calibration errors may be used to improve measurement accuracy using weighted data fit algorithms. The performance of the FGrabbit framework is continuously tested and has shown to be robust and scalable. Minor software development is yet carried out to improve usability for long-term accelerator operations.

APPENDIX

Circular Calibration Pattern

Circular calibration patterns are generally more robust (successful) than checkerboard patterns, e.g. when illumination is non-ideal, as shown in Fig. 8.

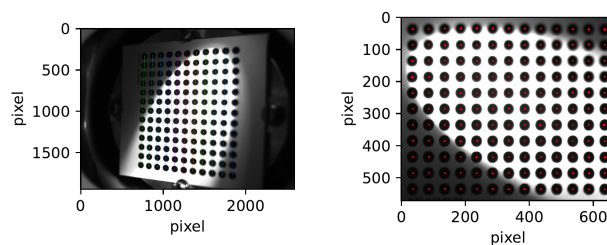


Figure 8: Screen with confined illumination and recognized pattern (left). Calibrated image using circular patterns including precision errors (right).

Virtual Calibration Pattern

Screens with sufficient markings for reference can be calibrated with a virtual pattern, e.g. created with a drawing tool and fed to the calibration algorithm, as shown in Fig. 9.

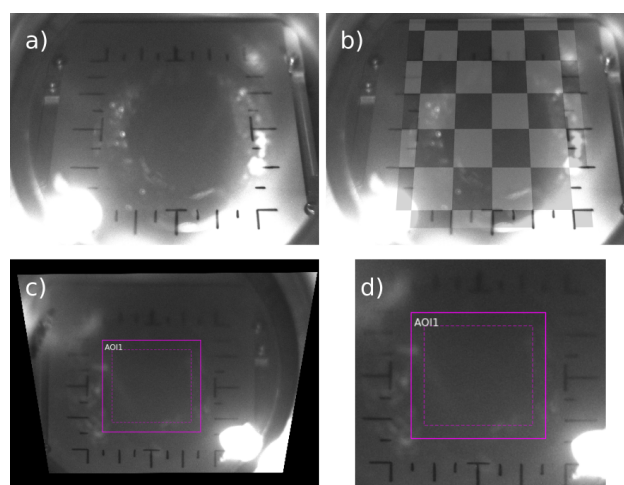


Figure 9: a) Sufficient visible markings may be used to create a b) virtual pattern for c) & d) image calibration.

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