Combining simulation and optimization: Multipurpose modelling of camera-based optical metrology systems

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When trying to build the best possible optical 3D sensor, there are a lot of different problems to tackle. In this contribution it is presented how particularly camera-based optical metrology and imaging systems can be calibrated, simulated, and optimized within a gradient-based optimization framework generalized for seemingly different objectives using the same differentiable model of the system.

1 Introduction

Camera-based optical metrology systems like stereo vision, fringe projection, deflectometry or light sectioning are widely used and well-established. However, when trying to build the best possible optical 3D sensor, there are a lot of different problems to tackle: What is the best sensor design? Where should the specimen under test be located? How should system parameters like the f-number be set? What are the best calibration parameters to describe the system?

As it turns out, these seemingly different optimization tasks are closely related and can be addressed using the same model of system behavior by only varying the parameters to be optimized as well as the specific loss function.

This contribution shows how especially driven by the current development of gradient-based optimization methods in the field of artificial intelligence, the same differentiable model can be used for multiple purposes in a generalized framework. It is presented how particularly camera-based optical metrology and imaging systems can be calibrated, simulated, and optimized with this approach.

2 Generalizing model-based optimization tasks

Due to their large parameter space and numerous technical constraints, optical metrology and imaging systems pose a wide variety of complex design choices. These should be made in an optimal way to end up with the best possible sensor for a given measurement scenario. Thus, tasks like finding the best sensor design, the best specimen pose, the best sensor parametrization and the best calibration parameters are all (often constrained) *optimization processes*. These seemingly different optimizations are usually approached separately, requiring a specific model for each task. However, instead of having to create a new model for each objective, the optimization tasks can be generalized by the gradient-based optimization framework outlined in Fig 1, using a *fully differentiable model of the system behavior*.

In general, the input of such a model of system behavior is a large parameter space (sensor parameters, calibration parameters, specimen parameters) and its output is simulated measurement data (e.g. camera images). This simulation alone is already an extremely useful tool in the design process. Preparing for gradient-based optimization, the model must

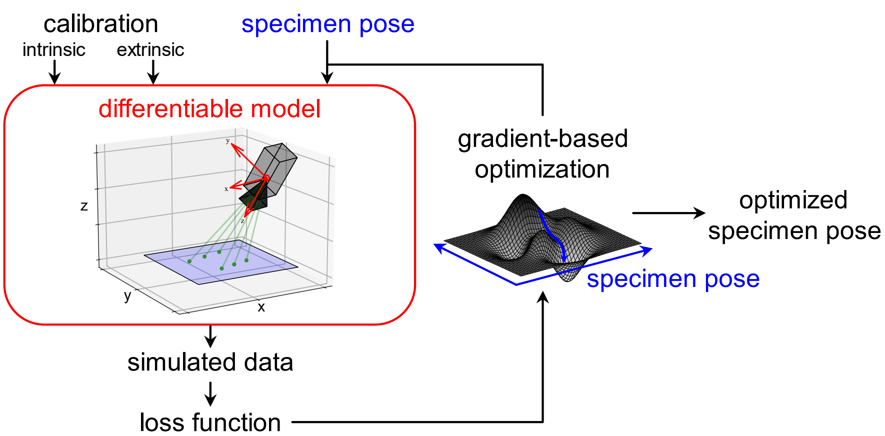

Fig 1 *Framework for generalized gradient-based optimization of camera-based optical metrology systems – in this example applied for optimizing the pose of the specimen for a fixed (given) sensor geometry.*

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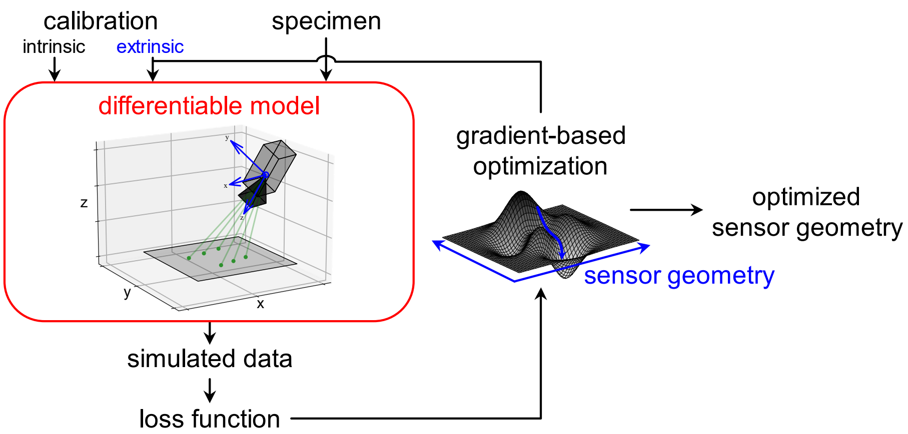

Fig 2 *The same framework (and model) applied for optimizing the sensor geometry for a given specimen.*

be differentiable, i.e., for all parameters entering the model, the gradient with respect to the outputs / loss function must be known. These gradients can be obtained by *symbolic*, *automatic*, or *numerical* differentiation. With such a model, optimization can be carried out for a wide variety of purposes by literally "connecting" a gradient-based optimization to the specific model parameters to be optimized, which runs backwards through the model (Fig 1). Of course, a corresponding loss function is required. In the configuration shown in Fig 1 for example, the specimen pose relative to a fixed sensor is optimized with respect to a loss function. Conversely, by simply "connecting" the optimization to the poses of the *system components* (extrinsic calibration) instead, the sensor geometry itself can be optimized for a specific specimen (Fig 2). In addition, by also "connecting" the intrinsic calibration and comparing simulated data with real measurements in the loss, the framework can be used for calibration (Fig 3). Note that the differentiable model is not changed at all despite the variety of optimization tasks.

3 Implementing differentiable models

Using platforms like *TensorFlow* or *PyTorch*, driven by the current development of artificial intelligence, can be very advantageous for implementing the differentiable model, as gradient-based optimization and tools like *automatic differentiation* are directly incorporated and provided "for free" in order to implement the backpropagation process commonly needed in these applications. Furthermore, with the *modularity* provided by concepts like *layers* and *trainable weights*, these platforms are perfecty suited for implementing the proposed framework.

4 Conclusion

It was shown how seemingly different tasks arising in the context of camera-based optical metrology and imaging systems like simulation, calibration or optimization can be generalized and implemented using the *same* differentiable model of the system behavior. Thus, accurately modelling the system behavior in a differentiable way may be very profitable, as it can be used directly for a wide variety of purposes.

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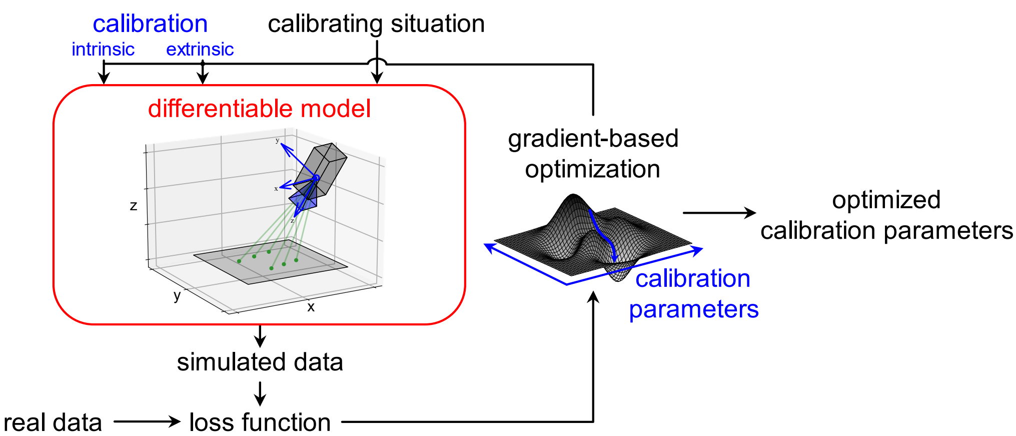

Fig 3 *The same Framework for generalized gradient-based optimization now applied for system calibration. Note that the differentiable model does not need to be changed at all despite the variety of optimization tasks.*