Numerical µ-CMM Simulation for the Application of Monte-Carlo Methods for the Uncertainty Estimation of Measured Dimensional Parameters

F. Meli, A. Küng
Swiss Federal Office of Metrology (METAS), Switzerland

Felix.Meli@metas.ch

Abstract

In recent years METAS has developed an ultra-precise, interferometer based, micro coordinate measuring machine (µ-CMM) with a unique 3D probe head with low, isotropic probing force. This instrument exhibits a single point measurement repeatability in the range of a few nanometers, even in scanning mode [1]. Using the commercial high level software Quindos, the instrument is applied to measure complex dimensional parameters of microparts. The exact estimation of task specific measurement uncertainties is almost impossible because there are many influences such as the measurement strategy combined with the applied fitting procedures inside the high level software. The application of Monte Carlo methods offers here a simple solution to this complex problem.

In this paper we present the numerical simulation model of the METAS µ-CMM and the application of Monte Carlo Methods for the uncertainty estimation of dimensional quantities of typical measurement applications.

1 The virtual µ-CMM model

The construction of the METAS µ-CMM machine is rather unique and especially designed for traceable metrology (see [1] for complete description). In operation, the probe head is standing still while the stage moves the workpiece in all directions around the probe. The displacement of all axes is measured with no Abbe offset as the interferometer beams always point to the center of the probing sphere. Due to this specific design, the virtual modeling of the µ-CMM requires only 6 main contributions:

1) The single measurement point repeatability is applied to single point probing and also to each of the scanning data points. Three independent Gaussian distributions are used for x-, y- and z-coordinates.

2) A linear length dependent contribution which sums up influences of sample expansion, air temperature as well as the scaling of the interferometer distance measurements (wavelength and cosine error). Three (one per axis) individual, length dependent Gaussian distributions.

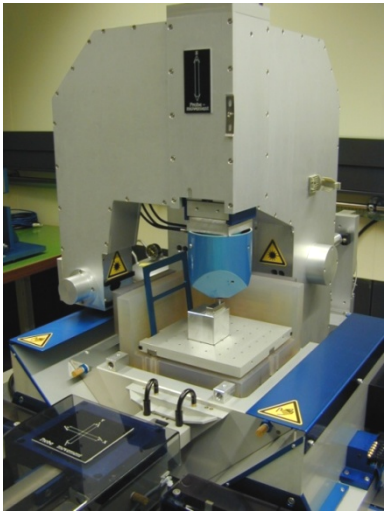

Figure 1: The METAS µ-CMM design simplifies the number of parameters to be implemented in the model.

3) The remaining uncertainty of the axis angles of reference mirror system after calibration. Three (one per axis) independent Gaussian distributions.

4) The flatness of reference mirrors after mapping correction. The model uses the flatness uncertainty (max amplitude) and an undulation period which characterizes the frequency of the deviation. The model uses sine waves of constant amplitude with randomized phase shifts. For the three mirrors 6 independent phase shifts are generated.

5) The shape of the probing sphere after calibration is modeled similar to the flatness of a reference mirror, i.e. with a constant amplitude derived from the sphericity and an angular undulation period. Also here two phase shifts are randomly generated.

6) Drift is included as a linear drift in an arbitrary direction. A Gaussian speed distribution and a homogenously distributed direction in space is used. The contribution uses the actual measured time stamp of the recorded measurements. With this contribution clever measurement strategies can be identified which are insensitive to linear drift.

For these 6 main contributions a total of 21 parameters are randomly generated. The magnitudes of the model parameters were estimated using the 63 contributions taken from the conventional uncertainty budget.

1.1 Model implementation

The simulation based on the described model needs a single recording of a real Quindos measurement procedure which delivers all required measurands for a specific sample. No CAD model is needed from the sample nor from the µ-CMM. Freeform scanning on unknown shapes can also be included in the measurement procedure. For the drift simulation a time stamp is added to each measured point during the recoding sequence. After the recording sequence the controller is switched to simulation mode while Quindos starts a loop to repeat the same measurement several hundred times writing the results to be analyzed to a file. A LabView program finally scans the result file and delivers for all measured parameters the average, the standard deviation min- and max-values. It shows histograms of the uncertainty distribution and also pair wise correlations of any two parameters. In order to run all automatically some commands were added to the communication between Quindos and the µ-CMM controller (Fig. 2). Some parameters are randomized for each point while other are randomized only once per measurement loop.

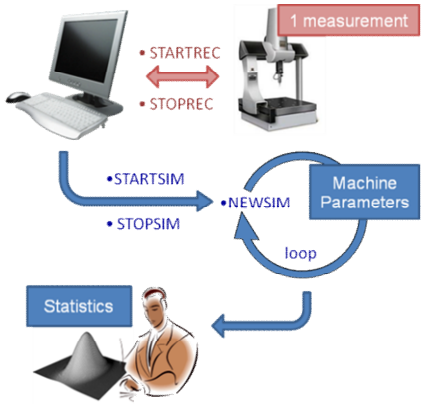

Figure 2: scheme of the communication between the Quindos high level language and the implemented µ-CMM model.

2 Virtual CMM validation with practical examples

The validation of the virtual CMM was performed with simple practical cases that can be easily verified analytically [2].

2.1 A circular segment

The uncertainty of the center position of a circle in a plane is highly dependent on the length of the arc segment measured. In figure 3 are the simulation results compared with analytical results for the case of 90° and 180° arc segments. To validate the simulation with the analytical model, only the point repeatability has been switched on (parameter 1), all other parameters have been set to 0.

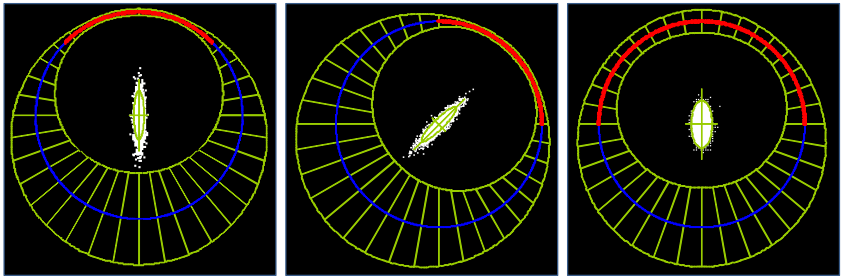

Figure 3: Comparison between Monte-Carlo simulation and analytical computation of the uncertainty of the centre position of 90° and 180° arc segments.

2.2 Influence of parameters and statistical distribution

Finding out how the different parameters affect the different measurands in 3D is definitively not straightforward. As it is easy to switch on or off any simulation parameter in the our virtual CMM, one can easily study their relative impact on different mesurands. For example, as shown in figure 4, some measurands may have an intrinsic non-Gaussian distribution that can be observed with the virtual CMM.

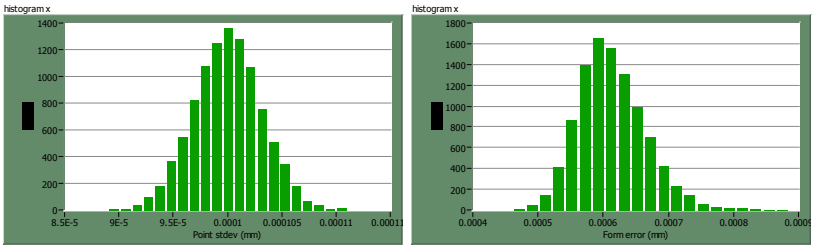

Figure 4: Simulation of a plane position with a Gaussian distribution for each of its points set to 100 nm (left) and the resulting plane flatness value (right) which has a non-Gaussian distribution.

3 Conclusion

The virtual micro CMM is an easy to use and very helpful to assess the uncertainty in 3D measurements. More than giving a single uncertainty value for each mesurand, it provides true insight for statistical distributions and the correlations between different measurands. The virtual CMM was validated using simple analytical cases.

References:

[1] A. Küng & F. Meli, Proc. 7th euspen Int. Conf., Bremen, May 2007, Vol. 1, p. 230

[2] Michael Hernla, Expert Verlag Renningen, 2007, ISBN 3-8169-2676-2