Automatically task-sensitive and simulation-based optimization of fringe projection measurements

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Abstract

Fringe projection systems gain importance in manufacturing quality control due to their multiple advantages. However, determination of an optimal inspection setup – including sighting- and positioning-strategy and configuration of the sensor – is a challenging task. There is no standardized, methodical approach established yet. Thus the success of an inspection depends on the skills and diligence of the inspection planner. This paper shows an approach for the reduction of these shortfalls. Therefore a software-tool was developed, which provides a simulation-based, task-sensitive and automatic optimization of inspection setups. Fundament for the simulation of the measurement is a continuous model. Thus the measurement result and the quality of a chosen inspection setup can be simulated. Based on this, algorithms for the multi-criteria-optimization of inspection setups were implemented.

Keywords: Fringe projection systems, simulation of measurements, inspection planning

1. Introduction

Fringe projection systems are increasingly used in industry for the inspection of workpieces due to short measurement duration, robustness and laminar data acquisition. They allow a holistic measurement of a workpiece with several million measurement points.

But there is one disadvantage: For each novel part the user has to plan the inspection process from the scratch. First, the fringe projection system has to be configured. Afterwards the position and orientation of the workpiece in the measuring field (measuring pose) has to be selected for each measurement. If it’s impossible to inspect all function bearing features in a single measurement, additional measuring poses have to be added and combined to a positioning- and sighting-strategy. Such strategy should ensure a holistic inspection, a minimal measurement uncertainty, a minimum of inspection time, efforts and costs. Regarding these multiple criteria, it’s very challenging for the inspection planner to find an ideal inspection setup via Trial-and-Error. This paper introduces a methodical and efficient software solution for the support of the inspection planner by automatically determining the ideal sensor configuration and sighting- and positioning-strategy.

2. Simulation of measurement

Figure 1 shows the basic model of a fringe projection measurement. A projector illuminates and encodes the object surface by use of a sinus-modulated fringe pattern with a phase value \( \Phi \). The fringe pattern is recorded by one or more cameras under the triangulation angle \( \gamma \), [1]. Camera- and projector-pixels are assigned to each other in consideration of the fringe width \( S_p \). The geometrical relations between the camera-pixels \( k \) and the corresponding projector-pixels \( p \) are determined during calibration, including the measuring angles \( \alpha_M \) and \( \beta_M \). The coordinates of \( M_K(x_K,y_K,z_K) \) in the camera-coordinate-system are calculated in consideration of camera constant \( c_K \) and optical lens distortion \( \tau_K \):
\[
M_K = \begin{pmatrix}
x_K \\
y_K \\
z_K 
\end{pmatrix} = \frac{b \cdot \sin \alpha_M}{\sin(\alpha_M + \beta_M)} \cdot \begin{pmatrix}
k_u + \Delta k_u \\
k_v + \Delta k_v \\
\sqrt{c_K^2 + (\tau_K \cdot k)^2}
\end{pmatrix} \quad (1)
\]

Figure 1. Geometrical model of fringe projection (Only one exemplary fringe displayed).

Figure 2 shows the model of the measurement, with a standard two-camera system, from the projection and detection of the fringe pattern over the phase calculation and allocation on to the calculation of the interim results \( M_K \) for each camera. Then the values of both cameras are combined and transformed to the world coordinate system \( W \), the final result of a fringe projection measurement is a point cloud \( X_{IND}(M_{1W}...M_{nW}) \), which includes measurements of \( n \) single points \( M \) on a workpiece surface. A detailed description of the underlying model was already given in a preliminary paper [2].

There are always influences on measurements that lead to deviations and to measurement uncertainties. It’s important to know that the influences on the fringe projection measurement vary at each measured point, so that the measurement uncertainty has to be calculated individually for each point. For details about the modelling of the considered influences, please see [2]. Most influences affect the phase calculation and the calibration. The close link between phase deviation and the measurement result is expressed by \( M_K(\delta \Phi_K) \). Here, deviations due to calibration \( (\delta \kappa) \) are calculated by use of the residual calibration error that is taken from calibration log. With the uncertainties due to ambience \( (\delta X_U) \) and software \( (\delta X_F) \), we receive the inverted cause-and-effect chain for a point cloud \( X_{IND} \) with \( n \) points:

\[
Y = X_{IND} - \delta X_U - \delta X_F - \frac{1}{2} \sum_{i=1}^{n} \left[ \delta M_{K1,i}(\delta \Phi_{K1,i}) + \delta M_{K2,i}(\delta \Phi_{K2,i}) + \delta \kappa_{K1,i} + \delta \kappa_{K2,i} \right] \quad (2)
\]

Fig. 2. Model of a measurement with a two-camera fringe projection system.
Now the measurement uncertainty for each measuring point can be determined compatible to GUM [3] by use of the sensitivity coefficients $c_{\delta \phi}$ for phase deviation. A conservative approach with only rectangular distributions is assumed. The equation for the combined standard measurement uncertainty for a single measuring point $M'$ results to:

$$u_c(M') = \frac{1}{\sqrt{3}} \cdot \sqrt{\delta X^2 + \delta Y^2 + \frac{1}{4} \cdot \left( \delta \phi^2_{K1} + \delta \phi^2_{K2} + c_{\delta \phi 1}^2 \cdot \delta \phi^2_{K1} + c_{\delta \phi 2}^2 \cdot \delta \phi^2_{K2} \right)} \quad (3)$$

3. Determination of ideal inspection setups

Inspection setups $S$ for fringe projection measurements consist of the following elements to be defined by the inspection planner:

- Positioning- and sighting-strategy (number of measurements and specification of measuring poses etc.)
- Sensor configuration (number of cameras, geometrical setup, software settings etc.)
- Workpiece handling (cleaning, matting, clamping etc.)
- Order of measurements (determines the changeover-time and -effort)

The multiple contradictory requirements to be fulfilled can be grouped in two categories:

- Technical requirements $t$: Holistic data acquisition, low measurement uncertainty, overlapping zones of datasets for data fusion, robustness, etc.
- Economical requirements $e$: Short inspection time, minimal inspection costs, minimal number of measurements, low sensor costs, low changeover efforts etc.

Because it is impossible to fulfill all requirements at the same time, there is an optimization problem with the purpose to maximize the degree of performance $P$:

$$S_{\text{IDEAL}} = P_{\text{max}} = f(t, e) \rightarrow \text{max} \quad (4)$$

This multi-criteria optimization can hardly be solved by an inspection planner, so there is a high demand for an automatic, computer-based determination of inspection setups. Basis for the introduced novel optimization method is the previously shown simulation of the measurement. Here, the quality of measurement setups is simulated, visualized and evaluated. The rating of economical aspects and calculation of $P$ is implemented, too. Following, two optimization algorithms within the software solution are introduced as examples:

Algorithm A: Holistic inspection

One crucial aspect in determining the number and properties of the measuring poses is the assurance of a holistic inspection. This iterative algorithm tries to maximize the measured surface zone at a minimum number of measurements. The result is then input for (4).

Based on a simulated measurement, surface zones $\tilde{x}_{\text{ADD},j}$ not yet recorded are selected and assorted by the difference of their normal vectors $\tilde{n}_i$ to the sighting vectors $\tilde{n}_{\text{SPS},j}$ of the fringe projection sensor at different measurements. The areas $\tilde{x}_{\text{ZUS},j}$ with the smallest vector differences to a sighting vector $\tilde{n}_{\text{SPS},j}$ are chosen. If $\tilde{x}_{\text{SPS},j}$ match already recorded nodes, then the end function $Z_{\text{hol}}$ is determined to

$$Z_{\text{hol}}(x) = \sum_{j=1}^{N} (x_{\text{SPS},j} + x_{\text{ADD},j}) \rightarrow \text{max} \quad \text{with side condition: } x_{\text{ZUS},j}(\tilde{n}_i) = \min(\tilde{n}_i - \tilde{n}_{\text{SPS},j}) \quad (5)$$

The new, optimized sighting vectors for each measuring pose are then calculated by use of a weighted averaging function. Each iteration ends with a simulation of the new inspection setup. If larger surface zones can be recorded, this sighting- and positioning-strategy is the basis for a new iteration loop (Fig. 3).
Algorithm B: Minimum Measurement uncertainty

Another optimization algorithm has the purpose to minimize measurement uncertainty (Fig. 3). This algorithm may be used separately or in combination with the previously shown algorithm. The idea behind this algorithm is to minimize zones that are recorded redundantly by two or more measurements. In return, the relevant dataset for optimization is reduced to surface zones with a yet high measurement uncertainty. Then the sighting vectors are optimized so that these areas can be measured with a reduced measurement uncertainty. The following necessary repositioning of the measuring poses is described in [4].

4. Sample: Automatic determination of a measurement setup

Fig. 4. Efficiency of the optimization algorithms (Simulated results at chosen setups).

The efficiency of the multi-criteria optimization for inspection setups is demonstrated. A demonstrator called ‘crossdie’ serves as sample. For weighting the requirements in the target
function (4), it’s assumed that a series of these parts should be inspected in a short time with a GFM ‘TopoCam mobile 500’ sensor. As the inspection task includes length, width and height of the cross, all sidewalls and the top surface must be measured.

Figure 4a shows the simulation of a random inspection setup (e.g. chosen by an inexperienced operator) with a single measurement. Of course, this means a minimum effort, but the measurement task cannot be fulfilled, as only some sidewalls can be measured. In contrary, an inspection by use of four measurements (Fig. 4b) would assure that 100% of the surface could be inspected with a very low averaged pointwise measurement uncertainty of only ±70 µm (k_p=2), but this inspection would need a lot of resources.

The task-specific optimal inspection setup was determined by use of the introduced optimization tool (Fig. 4c). Here, a sighting- and positioning-strategy with three measurements allows the inspection of over 99% of the surface with an averaged point wise measurement uncertainty of ±85 µm (k_p=2). This technically and economically suitable setup leads to the maximum performance P_max. The processing time for the whole automatic calculation was 1 minute (Compared to hours of trial-and-error an inexperienced user might need for this!).

5. Conclusion and outlook
Planning of component-compatible and economical fringe projection measurements at complex workpieces is a crucial challenge in praxis. Often this leads to an ineffective use of fringe projection sensors and a high risk of deficient inspection results. This paper introduced an approach for improving the situation. A simulation-based method for the automatic determination of ideal inspection setups, with focus on the task specific positioning- and sighting-strategy, was presented. This experimentally verified method allows the quick determination of multi-criteria optimized inspection setups for any workpiece, considering technical and economical aspects. In doing so, the inspection planning is independent from subjective, user-dependent influences. This leads to enormous cost savings, to a reduced time for inspection planning and to excellent and reliable inspection results.

By now, the user knows which measurements he has to perform to receive an optimal inspection result, but he does not know the order of the measurements. Thus the focus of future investigations lies on strategies to determine economically and technically appropriate orders of the measurements.

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References