Improvement of Data-Driven 3-D Surface Quality Inspection by Deformation Simulation

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Abstract—The automated visual inspection of complexly shaped, stamped sheet metal is a challenging task. Model-based methods are currently state of the art for surface quality inspection based on three-dimensional surface measurements. Data-driven models allow the representation of arbitrary three-dimensional surface shapes including possible tolerances and variation due to deformation.

Providing a sufficient amount of training data while ensuring adequate data quality is a time-consuming and laborious process. We propose a data driven three-dimensional surface model for quality inspection that allows the integration of deformation simulation in order to increase variance in training data. The effects of simulated data to the model quality are evaluated and results are given for data sets of automobile sheet metal parts.

Index Terms—3-D signal processing, surface quality inspection, data-driven modelling

I. INTRODUCTION

The objective of surface quality inspection is the detection of local defects like dents or bumps on arbitrarily shaped freeform surfaces. These defects lead to visible distortions in the reflection pattern of the painted surface, however they are hardly visible on the diffusely reflective surface right after sheet metal forming. Automated inspection systems based on optical three-dimensional (3-D) measurement systems with pattern projection acquire a high-resolution 3-D point cloud representation of the surface [1]. The processing of the 3-D data however is a challenging task.

The 3-D shape may vary globally in the range of millimeters due to manufacturing tolerances and deformation under varying placement on the measurement support. At the same time the local deviations to be detected lie in the range of down to 10 μm with surface details in the same order of magnitude [2]. Data-driven surface models are representations of typical surface shape including allowed variances. They are trained from a set of given reference measurements which are within tolerances and are based on manually assessed parts. A number of approximately 50 surface measurements may be sufficient to form a suitable surface model [2]. However, the data quality of the digital 3-D representation is crucial to the model quality. This introduces additional manual assessment and post-processing of the acquired data.

In this paper, we propose a data-driven surface model for surface quality inspection which allows the integration of deformation simulation. This artificially increases the amount of available training data, thus minimizing the required number of real-world measurements and the related manual processing.

II. RELATED WORK

Early inspection methods are based on two-dimensional (2-D) image processing and required manual setup of the image processing algorithms [3]. Deflectometry systems rely on image processing of a known reflection pattern [4] and are commonly used in the automobile industry today [5], [6]. However, these methods are applied in a later stage of the manufacturing process since they require a painted, reflective surface.

Automated 3-D inspection systems commonly rely on model-based approaches to data processing [7]. Photogrammetric measurement systems with pattern projection allow the acquisition of dense 3-D point clouds [8]. Time correlation methods, e.g. the phase shift method offer high lateral resolution [1], [9], they are thus well suited for surface inspection tasks [10]. The concept of the phase shift method has also been adapted to single-shot measurements, thus diverging from the time corellation principle [11].

Surface deformation has previously been considered by applying finite element method (FEM) for deformation simulation [12] or a similar finite element non-rigid registration [13]. In order to decrease the computational complexity of FEM simulation, approximative deformation has been applied and proven to deliver sufficient precision for surface inspection [14]. Data-driven surface models can be used more universally, since they require only a number of training measurements as a priori knowledge of the surface shape and variation [15]. Artificial neural networks have been used as surface models, using depth map data as input to the network [2]. Similarly, the control points of B-spline surfaces can be input to auto-associative neural networks or statistical models [16].

III. DATA-DRIVEN 3-D SURFACE MODEL AND DEFORMATION SIMULATION

A. Data-Driven 3-D Surface Model

Our approach is similar to [2], it uses range data (z-data on a regular x−y-grid) as input for model training. Principal Component Analysis (PCA) is then applied on the training data.
data. Projection of a measurement on the principal components yields the model parameters, this can be interpreted as a dimensionality reduction to the main variance components that describe systematic deviations within the training data.

The projection of a measured surface’s range data onto the variance components is described by

$$a_i = W_n \cdot z_i,$$

where \( z_i \) is the vectorised range data of the measurement under test and \( W_n \) is the matrix of the \( n \) most significant principal components. The back projection into the original range data space gives a representation of the measurement under test in terms of the trained geometric variation. This can be written as

$$\tilde{z}_i = W_{n}^{-1} \cdot a_i.$$

The resulting depth map \( \tilde{z}_i \) is similar to the measurement under test, however it does not include non-systematic variations, which are caused by surface defects. The comparison of the measurement \( z_i \) to its representation \( \tilde{z}_i \) thus allows the detection of surface defects. The model training corresponds to the computation of the principal components of the training data, which can be carried out by the eigen value decomposition

$$ZZ^T = W^T \cdot \Lambda \cdot W,$$

with \( ZZ^T \) being the covariance matrix of measured range data, \( W \) the matrix of all principal components and \( \Lambda \) the matrix of eigen values of the decomposition.

B. Deformation Simulation

The objective of the deformation simulation is to generate additional training data in order to reduce the effort needed to collect a sufficient amount of training data for the surface model. On the other hand, additional simulated data effectively improves the accuracy of the surface model with the same amount of training data.

An ideal simulation would accurately represent the production process. However this is not feasible due to the complexity of the process and the number of unknown parameters involved. We thus propose a simple physics-based deformation approximation based on the principle of spring-mass systems. Each 3-D point of the measured point cloud can be interpreted as a point mass with an assumed weight, interconnected to neighbouring points via springs as depicted in figure 1.

Deformation is executed by using an arbitrarily chosen master and slice part taken from the set of training data, and assigning corresponding point pairs between master and slice. The positions in space of corresponding points differ due to part variation, with a large difference indicating high variability. In addition to interconnected neighbouring points, springs are introduced between corresponding master and slice points (see figure 2), as well as between master points and corresponding slice points normal to the surface.

IV. EXPERIMENTAL RESULTS

A total of 95 real measurements based on a phase shift measurement were available for training and testing of the proposed method. Measurements for a car door panel and a segment of a front hood were considered (see figure 3). The measurements lie on a \( 1 \text{ mm} \times 1 \text{ mm} \) \( x - y \)-grid and are given with a \( z \)-accuracy of approx. \( 10 \mu \text{m} \).

A. Evaluation of Point Interconnection

To test the effectiveness of different point interconnections, the following types of point neighbourhoods have been tested:

- **00** - no point interconnection
- **10** - 4-neighbourhood
- **01** - 4-neighbourhood, diagonal
- **11** - 8-neighbourhood

This allows the generation of new parts by matching different pairs of training measurements as master and slice, and observing a number of time steps between the suspended state and the equilibrium state. Additionally, simulation parameters (e.g. weight and weight distribution of masses, elastic modulus of springs, type of point interconnection) may be changed to introduce additional variability in the generated parts.

Fig. 1. Interconnected spring-mass systems (right) between 3-D points of a measured car door panel (left).

Fig. 2. Interconnected spring-mass systems (right) between a master measurement (left) and a slice measurement (center) of a car door panel. Deviations of slice and master are visualized by a color-coded point cloud (center).

Fig. 3. 3D visualisation of a measured car door panel (left) and segment of a car front hood (right).
Between master and slice, interconnection along $z$-direction as well as along normal direction are designated by letters $Z$ and $N$, giving a total of 8 interconnection variants $Z00$, $Z01$, ..., $N11$. A total of 6 real part measurements have been used for generating 180 virtual parts (= 6 parts $\times$ 5 permutations $\times$ 6 time steps), with the remaining 89 real part measurements begin used for evaluation of the method. The surface model has been trained with only 6 real part measurements as well as with the 180 simulated measurements, and $n = 6$ principal components.

Results can be visualized for single measurements as error maps, where the error between the measurement under test and the model output $z_i - \tilde{z}_i$ is color coded. Figure 4 shows such error maps for a surface model of a car door panel with and without simulated data. A qualitative assessment of the remaining model error shows improvements especially along highly curved areas, e.g. along the top design ridge and the door handle cup. As a quantitative measure, the difference in maximum model error per error map has been chosen and has been computed as a mean for the remaining 89 evaluation parts (see figure 5).

The interconnection along the surface normal direction yields a significant improvement of the model, with a 4-neighbourhood giving an improvement of roughly 25% ($37\,\mu m$ down from an absolute maximum error of $151\,\mu m$). The part is of lesser geometric complexity, it is mostly flat apart from a design ridge. The overall model error is thus significantly less compared to the car door panel, and the reduced complexity leaves less space for improvement.

**B. Evaluation of Number of Training Samples**

With an increasing number of training samples, the number of possible permutations and thus the number of simulated parts vastly increases. In order to evaluate the effect of the number of training samples, the measurement data set has been split into 45 training measurements and 50 test measurements. From the training measurements, simulated training data has been generated using our proposed method with $N01$ connection and two simulation time steps, resulting in up to $3960$ training data sets. The surface model has been trained with the training data resulting from 5 up to 45 real measurements.

The average of the absolute maximum error is given in figure 7. The effect of additional simulated parts is mostly visible for few real training samples. Starting from 15 real measurements, the improvement due to added simulation data declines; it even causes a deterioration in model quality. However the overall model quality does not improve for more than 20 real measurements, meaning that the variation in surface geometry can be sufficiently represented by 20 degrees of freedom.

**V. CONCLUSION**

We presented a data-driven surface model for surface quality inspection which allows the integration of deformation from an absolute maximum error of $70.9\,\mu m$).
The proposed deformation simulation allows a very efficient computation, and is used to generate additional training data to increase model accuracy. The improvement of the model error depends on the complexity of the surface geometry. Parts with high-curvature details benefit significantly from the additional simulated data. Improvements by 12%, up to 25% could be shown for two different real world measurement series. The benefit of simulated data sets decreases with the number of available real training measurements.

The proposed method is thus a useful tool in applications with very few available measurements. It can also be used to bootstrap a surface model from few training samples, adding additional training measurements online.

REFERENCES


