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Framework for the monitoring of complex surfaces based on optical assessment

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The optical perception of surfaces manufactured with high precision is an important quality feature for most products. The respective manufacturing process is rather complex and depends on a variety of process parameters which have a direct impact on the surface shape and topography in the most cases.
Surface-shapes, topographies and colorings are mostly measured using classical methods (roughness measuring device, gloss measuring device, spectrophotometer, computer tomography, or tactile coordinate measuring instruments). To improve the conventional methods of condition monitoring, in this case represented by the monitoring of the surface, a new image processing approach is needed to get a faster and more cost-effective analysis of manufactured surfaces. For this reason, different optical techniques based on images have been developed over the past years.
In this paper, a framework for surface monitoring is outlined and discussed in detail according to every single step along the monitoring process. For this purpose, the study differentiates between the application of the descriptive statistics as well as the application of artificial intelligence. Both applications are mainly based on the same data sources, though on different sample sizes and provide answers to differing questions that often complement each other.

Keywords: Surface monitoring, statistics, machine learning, surface measurements, optical measurements.

1. Introduction

Digitalization and the continuous improvement of Industry 4.0 in the production of technical products have enabled increasingly comprehensive data acquisition within the individual processes over the last few years. This has made it possible to implement complex and more precise data-based analysis procedures. Based on the data, multivariate models, such as methods of Inference Statistics (IS) or Machine Learning (ML) algorithms, can be developed to capture multi-dimensional, complex relationships and determine their influence on achieving defined process goals. Implementing these models on the running processes enables the recording of the quality of the products within the manufacturing process. As a result, parameter settings can be adjusted during production, rejects can be reduced, and the quality of the final product can be guaranteed. Such methods can create a solid foundation for continuous process optimization and the constant improvement of quality management. As digitalization and data collection are expected to continue gaining importance in the manufacturing industry in the coming years, it makes sense to use this data by implementing such methods in the processes within the framework of quality management.

This paper outlines and discusses in detail a framework for surface monitoring according to every single step along the monitoring process. The study differentiates between the application of IS as well as the application of Artificial Intelligence (AI) or, in particular, ML. Most applications are based on the same data sources but on different sample sizes and provide answers to various questions that complement each other. In the case of the application of ML algorithms, the proposed framework distinguishes between supervised, semi-supervised, and unsupervised learning techniques based on various data and the availability of the target values or classes.

Since data is one of the key elements, the influence of the amount of data, data quality, and data structure are discussed with regard to the uncertainty of the models and the final results. Furthermore, the influence of the mentioned measurements, usually used as target variables, on the results is also discussed.

This paper has a generic character and can be applied to many technical products. Nevertheless, many of the single steps of the framework are explained based on joint projects realized in common work of academia and industry over the past decade.

2. Classical approach and it's challenges

The aim of this framework is to improve the manufacturing process by implementing data analysis methods. Figure 1 illustrates the classical manufacturing process and the associated quality assessment or monitoring process in the context of producing technical products. A raw part is manufactured with a fixed set of adjustment parameters, and the quality is inspected and evaluated based on empirical experience and subjective assessment after the production process. The products are then sorted into good quality, approved products and rejects. One of the quality management objectives is to reduce waste and associated costs. The setting-parameters relevant to the manufacturing process have a direct influence on the quality of the final product. However, a simple standardized parameter setting can only be defined to a limited extent due to environmental conditions, wear of individual components, and production-related differences such as the type of raw parts or the material used. Therefore, a constant process improvement is aimed at by optimizing the choice of setting parameters within the framework of this research work.

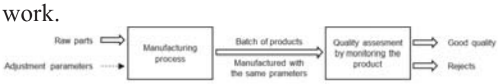

Fig. 1. Classical manufacturing process and the associated quality assessment in form of monitoring process

The characteristics of the product, such as roughness, shape, topography, gloss, or colouring, can be measured to create an objective quantification. However, classical methods for measuring these characteristics are time-consuming and expensive, and alternative methods must be used for implementation.

In addition, demographic changes and the lack of experience among young employees pose a challenge for many companies. In this case, an automated and data-driven solution for monitoring product quality may provide a suitable solution.

3. Framework for the monitoring of surfaces

In Figure 2 the planned, improved, and data-driven framework of the manufacturing and quality assessment process in production of technical products is shown. This approach is based on the PDCA quality control cycle.

The first step involves selecting the process parameters, which are recorded as input data for further analysis. In order to determine the quality of the surfaces, a measurement-based procedure (cf. section 4) with data-driven methods (cf. section 5 and 6) are to be used. If the quality meets the requirements, it is passed on to the next step. However, if the surface is judged as a reject, the setting parameters need to be adjusted for subsequent batches. In addition, an adjustment parameter setting is to be determined with which the quality of the assessed product can be reworked in order to achieve the quality standards. The last step is only possible if the quality allows for rework; otherwise, the product needs to be disposed of.

The use of data-driven methods is also planned for these two process steps. In contrast to the process described in section 2, in which an entire batch is manufactured and assessed (cf. Figure 1), the quality assurance in the adapted process is assigned to the manufacturing process of an individual product. In this way, discrepancies in the setting parameters are detected at an early stage and immediately adjusted. This minimises the effort to rework initial rejects and leads to cost reduction.

In Figure 2, the white boxes represent the steps of a classical process, the green boxes are the data-driven approaches, and the red ones represent the novelty of the proposed framework. The main advantages of the proposal are the full automatization of the process, significantly reduced demand on the participation of an employee as well as significantly reduced need of his experience, and finally the possibility of full documentation of the manufacturing process and the product's quality itself.

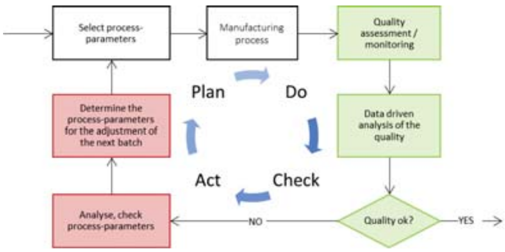

Fig. 2. Improved, data driven manufacturing process and the associated quality assessment in form of monitoring process

4. Measurements

The basis of any data analysis is the availability of measured values that have been recorded with regard to the surface topography to be examined. For the measurement of surface topographies or component geometries, various measurement systems have become established in industrial applications.

4.1. *Measurements systems*

The most important universal measurement systems which were used in the context of the present research work to obtain measurement data as the basis for Inference Statistics and AI-based data analysis of components, are briefly outlined below:

- Coordinate measuring technique; measurement of geometric parameters of simple and complex components; operation in the measuring laboratory (often under air-conditioned conditions); measurement result: component geometries, conditionally (depending on the gauging head) also surface topography parameters.
- Surface and contour measurement system: The starting point of a probe system is a transducer with which the surface profile sensed by the probe tip is converted into an analogue electrical quantity; a distinction is made in gauging head systems between the following setups: Reference surface touch probes, skid-type touch probes. Measurement result: Surface topography characteristic values
- Circular and cylindrical form measurement: Form testing devices are measuring devices with which the form deviations of certain components are recorded and evaluated with high accuracy. Measurement result: component geometries and surface topography characteristic values
- Computer tomography (CT): CT is an imaging procedure. In contrast to X-ray tomography (pure radiography), CT uses a computer to digitally calculate sectional images from the absorption values of X-ray signals that pass through the body from different directions. The sectional images can be calculated into a 3D model. measurement result: internal/external component geometries.
- Optical and optoelectronic measurement systems:
  a) Measuring microscope: Measuring objects in transmitted light (2D): stamped and bent parts, plastic parts, external threads, gear wheels, seals; measuring objects in reflected light: Surface fittings, surface finishes (3D).
  b) Photogrammetry (3D): Calculation of three-dimensional coordinates based on images taken from different directions. Measurement result: component geometries.

4.2. Measurement uncertainty

A decisive influence on Inference Statistics and AI-based data analytics is the measurement uncertainty that is assigned to the measured values depending on the measurement method. Large measurement uncertainties lead to possible false detections or misinterpretations - for example in component assessment or anomaly detection. The following fundamentals must be considered cf. (Radetzky 2021a) and (Radetzky 2021b):

1) The measurement uncertainty U is a parameter associated with the measurement result Y that characterises the dispersion of the values that could reasonably be assigned to the measurand.
2) The measurement uncertainty U is a measure of the possible measurement deviation of the estimated value of the measurand determined as measurement result Y.
3) The measurement uncertainty U is an estimated value to characterise a range of

values within which the true value of the measurand Y lies.

5. Statistical analysis

5.1. *Inferential Statistics in the analysis and assessment of surfaces: Approach*

The methods of inferential statistics offer extensive possibilities for the analysis and evaluation of component surfaces. The following approach including basic steps is carried out for this purpose.

A) Development of a reference baseline

1) Determination of the function-critical and safety-critical component features on the basis of which the surface can be characterised (e.g. roughness values Ra, Rz, Rsm, and gloss).
2) Definition of reference component classes with different properties.
3) Recording of series of measured values - using suitable measuring systems (cf. Sec. 4) - to represent reference component classes with different properties.
4) Mapping the features of the component classes.
   a) Parametric: reference distribution models
   b) Non-parametric: reference values

B) Analysis and evaluation of component surfaces

1) Measurement of the test object on the basis of defined function- and safety-critical components.
2) Comparison of the condition of the test object and the condition of the reference component classes, considering the measurement uncertainty (cf. Sec. 4.2).
   a) Two-sample comparison: parametric or non-parametric; e.g.: mean value and dispersion.
   b) Multi-sample comparison: parametric or non-parametric; e.g.: mean value and dispersion.
3) Result: Evaluation of the component surface by assignment of a reference component class with indication of significance levels and measurement uncertainty consideration.

5.2. *Function and safety-critical features*

When analysing the technical reliability of a product or a process, function-critical and safety-critical characteristics often represent the starting point of the analysis (Bracke 2022). In the context of the present explanations, function-critical characteristics are understood to be all characteristics that are of particular importance for the central functions and for the reliability of a component, an assembly or a system. Function critical features are often considered within the tests to be performed during component manufacture. The inspection procedures may be: random sampling, Statistical Process Control (SPC) or full inspection.

Safety-critical features include all features that, in the event of a deviation from their specification, lead to a fault that endangers users respectively people. Therefore, safety-critical characteristics in series production are monitored, for example, with a (non-destructive) full inspection

5.2. *Methods of Inference Statistics*

Since the analysis and evaluation of component surfaces focuses on the comparison of the condition of the test object and the condition of the reference component classes, this chapter focuses on the two-sample case and the multiple-sample case.

5.2.1. *Hypotheses*

Fundamental to the comparison of test object and reference component class on the basis of function/safety-critical characteristics is the investigation of mean value and dispersion (cf. Table 1):

Two distributions F and G have the same shape (null hypothesis), but differ in a location parameter Θ (alternative hypothesis H1):

$$H_0 : G(z) = F(z); \quad H_1 : G(z) \neq F(z - \Theta)$$

Two distributions F and G differ regarding to variability (alternative hypothesis H1):

$$H_0 : G(z) = F(z); \quad H_1 : G(z) \neq F(\Theta z)$$

Two distributions have the same shape, but differ in a location parameter Θ (alternative hypothesis H1):

$$H_0 : F_1(z) = F_2(z) = \cdots = F_c(z) = F(z)$$
$$H_1 : F_i(z) \neq F(z - \Theta_i)$$

Two distributions differ in the variability (alternative hypothesis H1):

$$H_0 : F_1(z) = F_2(z) = \cdots = F_c(z) = F(z)$$
$$H_1 : F_i(z) \neq F(\Theta_i z)$$

Table 1. Selection of statistical significance tests for the comparison of the condition of the test object and the condition of the reference component classes (two and multiple sample case)

Two sample case		
Mann-Whitney-U Test	Comparison of two centroids	parameter -free
Siegel-Tukey Test	Comparison of two dispersions	parameter -free
Levene-Test	Comparison of two dispersions	parameter -free
t-Test	Comparing two mean values	parametric
F-Test	Comparison of two variances	parametric
Multi-sample case		
Kruskal and Wallis test	Comparison of several centroids	parameter -free
Post hoc analysis according to Conover	Detection of the centroid, which deviates in a multi-sample comparison	parameter -free
Bartlett-Test	Multiple variance comparison	parametric
Jonckheere and Terpstra-Test	Comparison of several samples with regard to a trend behaviour	parameter -free
Meyer-Bahlburg-Test	Multiple variance comparison	parameter -free

6. Machine Learning

As stated in (Hinz 2018) ML is (in addition to planning, reasoning, natural language processing, perception, creativity, etc.) a branch of AI with the aim of predicting of unknown events or scenarios that are unknown to the computer at the present time. It gives the machine the ability to learn from experience without being explicitly programmed (cf. Witten 2001). Furthermore, ML is a field of data mining, since it is a process of solving problems by analysing data already present in a database and discovering patterns in this data. Basically, ML can be categorized with regard to the following categories (cf. Awad 2015):

- Supervised learning: A mechanism that concludes the underlying relationship between the observed data (in this case the attributes or input data) and the target class (or target variable). The learning task uses the training data to synthesise the model function and tries to generalize the underlying relationship between the input and the output.
- Unsupervised learning: Designed to discover hidden structures in unlabelled datasets. Here, the outputs are unknown at the time of the analysis. The general approach involves training through probabilistic data models. The most popular examples are clustering and dimensionality reduction.
- Semi-supervised learning uses a combination of a small number of labelled and a large number of unlabelled datasets to generate a model function or classifier. Because the labelling process of acquired data requires intensive skilled human labour inputs, it is expensive and impracticable. In contrast, unlabelled data are relatively inexpensive and readily available. Semi-supervised ML methodology operates somewhere between the guidelines of unsupervised learning (unlabelled training data) and supervised learning (labelled training data) and can produce considerable improvement in learning accuracy.

There are also further branches of ML, such as reinforcement learning (a methodology that involves exploration of a sequence of actions or behaviours by an intelligent agent in a defined environment with the aim to maximize the cumulative reward) but since they don’t find an application in the presented framework, they will not be discussed in this paper.

6.1. *Supervised learning*

As already stated, supervised learning generalizes the underlying relationship between the input and the output. The relationship can be stated in form of classification (in case of classified variables) or regression (in case of continuous variables) analysis. For both classes of problems exist different algorithms which will be discussed in the following.

The key difference between supervised and unsupervised learning is the availability of the target variables. These target variables can be subdivided in quality monitoring according to the type of data:

- Single variables represented by integers, floats, characters, or strings
- Signals represented by a development of a single variable, e.g. a vector of integers
- Pictures

As a matter of course, both single variables and signals can be used in univariate and multivariate way.

Due to the mentioned applications and data types, following algorithms can be used for the quality assessment (excerpt):

- Classification problems with single variables as targets:
    - Logistic regression
    - Decision trees (Hinz 2019)
    - Random Forest algorithms (Hinz 2022a)
    - Support Vector Machines
    - Neural Networks (Hinz 2021a)
- Regression problems with single variables as targets:
    - Regression analysis
    - Regression Trees
    - Random Forest algorithms (Hinz 2022)
    - Support Vector Regressors
    - Neural Networks (Hinz 2021)
- Classification and regression problems with signals as target variables:
    - Recurrent Neural Network with different architectures. The most common are Long-Short-Term-Memory algorithms (LSTM) (Hinz 2022b)
- Classification and regression problems with pictures as target variables:
    - Convolutional Neural Networks (CNN)

6.2 *Unsupervised learning*

Since the target variables (as well as their types) are missing in case of unsupervised learning, there is no need for differentiation between classification and regression problems. Here, as already stated, the aim is the search of hidden structures in unlabelled datasets. Nonetheless, these algorithms can be also divided in different groups based on the underlying concept for grouping the structures:

- Algorithms based on the distances between the input variables like k-Means (Hinz 2022c)
- Algorithms based on the concept of distribution functions line Gaussian Mixture Models (GMM) (Hinz 2022d)
- Density based approaches like DBSCAN (Density-Based Spatial Clustering of Applications with Noise)
- Hierarchical clustering (Awad 2015)

6.3 *Semi-supervised learning*

Semi-supervised learning is a very powerful learning technique especially when the cost of labelling is too high. This is very often the case in many industrial applications, in particular when the processes are changing and the underlying data varies between them. One of the solutions is the application of the Yarowsky algorithm, as shown in (Brueggemann 2022).

7. Data preparation

All the presented methods in algorithms (with regard to IS and ML) perform only as good as the quality of the data provided for the analysis process. Moreover, a good model does not provide valid results with poor data-quality.

One of the major problems is the uncertainty in the data and in the models. This can have many reasons such as the data quality (e.g. used variable types, NaN handling, missing values, amount of data), mathematical models (e.g. optimization algorithms, parameter estimators, underlying distribution functions), or empirical knowledge about the models (use cases, network architectures, and hyperparameter tuning of the algorithms). Some of the mentioned problems are described and quantified in (Hinz 2015).

A further challenge in case of the application of many of the ML algorithms is the feature extraction. In many cases this is the most time-consuming part of the overall analysis. The description of the features as well as their extraction is problem-based (i.e varies from one case to another) and is out of the scope of this paper. For comprehensive information refer to (Guyon 2006) and (Liu 1998).

7. Conclusion

This paper presents a method for quality monitoring of technical products. The steps presented for process optimization are part of a comprehensive quality assessment based on the PDCA cycle for continuous improvement, aimed at achieving the quality objectives. An important component of the process optimization presented is the use of information systems (IS) and machine learning (ML) algorithms to assess the quality of the product. Furthermore, this paper presents an improved method for the data-driven manufacturing process.

This paper demonstrates a wide range of application possibilities of many algorithms in both IS and ML domains. The algorithms are discussed in terms of their applicability based on the underlying data. Finally, the challenges regarding measurements and data uncertainties are discussed in detail.

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