Towards Automated Visual Inspection and Classification of Micro-Parts

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Abstract: The mechanical manufacturing of micro-parts is a challenging field of research. Because of high quality requirements and small tolerances, manufacturing processes have to be very stable and precise. In order to achieve high precision a suitable quality assurance concept is required. Only measured features can be used for statistical process control (SPC). Therefore, this paper presents a concept of an automated visual inspection and classification methods for micro-parts. Using confocal laser scanning microscopy, high-resolution 3D-height maps with depth selectivity are obtained. The identification of surface imperfections is done with a set of conventional image processing techniques. Afterwards, these kinds of surface defects are classified by the use of classification methods like decision trees.

Key-Words: Micro-Production, Deep-Drawing, Machine Vision, Quality Control, Height Maps

1 Introduction

Micro systems technology is one of the most important cross-sectional technologies and the trend of miniaturisation will last the next decades [1]. In comparison to chip manufacturing and the use of Lithographic technologies like LIGA-processes, mechanical micro manufacturing is not very advanced. Therefore, the development of micro manufacturing technologies and micro production concepts is still an active field of research. The Collaborative Research Center (CRC) 747 is an interdisciplinary research project involving eight institutes of the University of Bremen and focusing on micro forming. The most challenging issue of high performance micro processes is the balance of accuracy and efficiency [2]. Requiring high precision, the process configuration is very complex and time-consuming. The use of machine vision techniques should support the process configuration and assure the process reliability. Conventional vision-based quality inspection systems primarily rely on two-dimensional detection and shape estimation algorithms. More advanced vision-based quality inspection systems employ three-dimensional methods in order to detect production errors more reliably and robustly [3,4]. This paper outlines a machine vision based quality concept for the surface inspection of micro-parts which are manufactured in the CRC 747 using three dimensional height maps. With identifying the systematic surface defects, our focus is the analysis of possible causes for the fast adjustment of the process parameters.

2 Comparison between macro and micro manufacturing

The application of macro processes on the micro fabrication is not thoroughly feasible. For example, Vollertsen examined the deep drawing of micro-cylindrical flange cups in comparison to macro-ones with the same shape [5]. The result showed that only the flange of the micro-cups had small wrinkles. Therefore, relevant differences and distinctions between micro and macro forming are discussed in the following.

2.1 Size-effects

The major distinction that exacerbates downscaling of conventional macro metal-forming processes to the micro-level is based on micro size-effects [6,7]. At micro-level, material behaviour is changed. The influence of the single grain size increases and the material can no longer be considered as a homogeneous continuum. It was suggested that the material response is dominated by the size and orientation of individual grains. Fülöp showed in the simulation of an uniaxial tensile test and a three-point bending test, that the yield stress decreases, when the grain size is less than the thickness of the ultra-thin metal sheet [8]. In contrast, the yield stress increases, when the grain size is larger than the thickness of the sheet. We can conclude that we have different material behaviour in addition to the thickness of the sheet. This means that conventional models as well as analytical and empirical methods cannot simply be transferred to micro manufacturing. Vollertsen proposed five types of size-effects [9]:

Pure volume size-effects: A decreasing volume of the micro-part causes a decreasing number of micro structural features which can change the failure probability distribution for a specific lot of parts.

Surface to volume size-effect: Decreasing part volume cause an increasing ratio surface to volume. Hence, surface effects become more important, especially if only a fraction of the surface is involved in the process.

Forces relation size-effects: The van der Waals forces and the surface tension are very small in comparison with gravity and can be neglected in conventional macro processes. In terms of micro forming they have to be considered because they are relatively significant compared to the required process force.

Grain size to thickness size-effect: The grain size is generally associated with the material properties and determined by the casting condition. It is impossible to generate various materials with identical grain structures. The grain size cannot be scaled down like e.g. part dimensions.

Surface structure scalability size-effect: The surface structure cannot be downscaled like the part dimensions. For example, lubrication may not used on a micro-part, because the surface structure does not allow the creation of lubrication pockets and the frictional resistance increases with the downscaling.

2.2 Measurement uncertainty and tolerances

The exact knowledge about geometry, forces and surface roughness or flow characteristics is required to guarantee high quality (micro) products. The development of a quality control concept that integrates all of these aspects is a challenge and probably the reason why quality control in microtechnology has not been completely established yet [10]. The major quality characteristics are dimension and surface properties. The impact of calibration problems, repeat accuracy and measurement uncertainties have to be considered.

Micro manufacturing processes are characterized by high process variability and increased significance of measurement uncertainty [11]. The measured data is always a result of a superposition of process variation and measurement variation. According to DIN ISO 21747, process performance and capability statistics have to be measured. By using SPC (Statistical Process Control) also high production volumes with millions of micro-parts can be controlled. Because of long measurement times, a 100% quality check cannot be implemented and the quality assurance has to focus on using probes.

Another aspect is the relationship between processing tolerances and metrology methods in micro technology. Significantly small tolerances are a result of small part dimensions in micro forming [12]. In order to verify tolerances which are necessary to ensure product functionality, the measurement needs to be sufficiently exact. In general, measurement uncertainty becomes larger while the tolerance conformance zone for process variations becomes smaller.

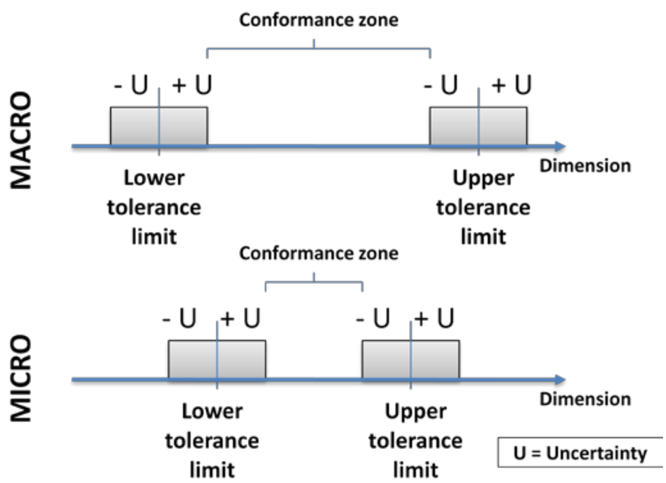


Figure 1: Illustration of relationship between tolerance and measurement uncertainty [13].

The reduction of the conformance zone in the micro dimension due to a constant measurement uncertainty is shown in Figure 1.

2.3 Quality control

The second aspect which offers a difference between macro and micro manufacturing is the quality control. Results and experiences with existing methods and techniques cannot easily be transferred to the micro dimension. Resolution, measuring range and image quality restrict the applicability in the field of microtechnology.

Furthermore, the dimension of the micro-parts in the manufacturing processes makes measurement essential because it is the only accessible way to the micro dimension. Machine Vision techniques are essential to evaluate the results from the metrology system. Classical image processing methods applied in automated quality inspection in the macro range [14, 15] were adapted to the micro world working on a high resolution image.

The biggest issue in quality control of micro manufacturing processes is the lack of production accompanying methods such as customized statistical process control for micro manufacturing. Such methods have to consider that we have higher uncertainties of geometric measurement in micro manufacturing. Sometimes we have to deal with unstable processes, which cannot be qualified for normal SPC.

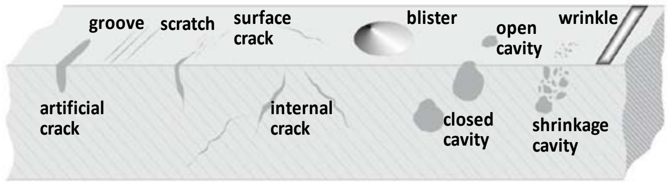


Figure 2: Types of material defects [16].

One of the most important measurement aspects is observing the shrinkage. It discloses the reproducibility of the fabrication technique [17]. Referring to the classification of different types of material defects, Figure 2 shows a general view with schematic examples. Referring to the non destructive testing concept of this paper, especially the surface imperfections mentioned in DIN ISO 8785 like cracks, grooves, scratches and blisters are the objects of this study. For these kinds of defects, the confocal microscopy provides a good measurement tool by generating height maps of the surface.

3 Surface inspection of a micro-cup

The objective of the CRC 747 is supplying processes and methods for the mechanical forming of metallic micro components. This is realised with comprehension of the essential aspects of the forming process - from substance development to component testing [19]. The procedure of the developed surface inspection process is illustrated in Figure 4. The examined micro-part “micro-cup” is the product of a deep-drawing process, which is manufactured at the Bremer Institut für angewandte Strahltechnik (BIAS). An image of this micro-cup acquired by a scanning electron microscope is shown in Figure 3. Especially deep-drawn parts cause many problems in surface inspection, because even smallest impurities in the raw material induce crackings, blisters and cavities during the process.

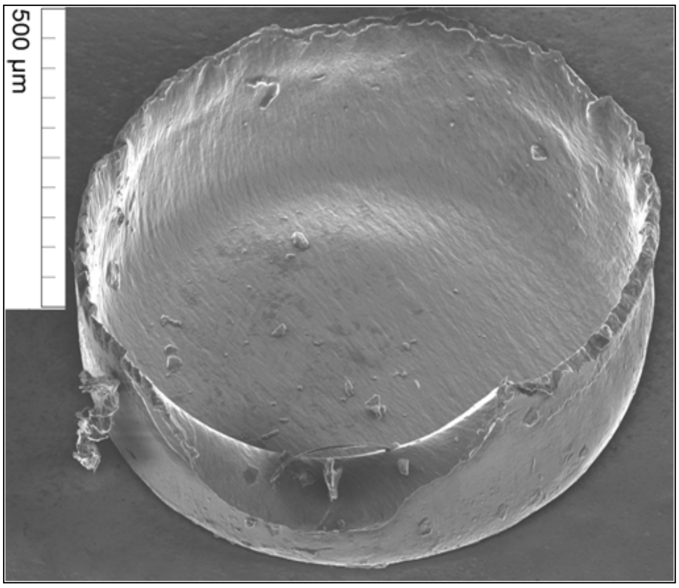


Figure 3: Sample of deep-drawn “micro-cup” front (BIAS)

The marked pathway in Figure 4 describes the structure of the actual approach. The investigated micro-cup was manufactured in a micro forming machine (MUM), which is illustrated in Figure 5. The final version of the automated classification system includes the DHM measurement system, which is used to generate high-dimensional image. Additionally, the manufacturing of the micro-cup is simulated by a three dimensional point cloud. The simulated object is used as a referring object. The simulation is performed in order to be able to merge the information from the simulation and the generated image from the DHM measurement system. The result is also a three dimensional height map. The measurement system is a confocal laser microscope, which generates high-resolution three dimensional images. Based on these images, position and shape deviations on the surface of the micro component should be identified and finally classified with an artificial neural network. The detection of surface defects for quality assurance is one of the most challenging and complex problems of industrial image processing [18]. The surface can be inhomogeneous and brightness fluctuations are common. Anyway, the objective is to detect the defects without identifying regular objects as failure parts. In the following sections, our approach of surface testing for the quality evaluation within the CRC 747 is shown.

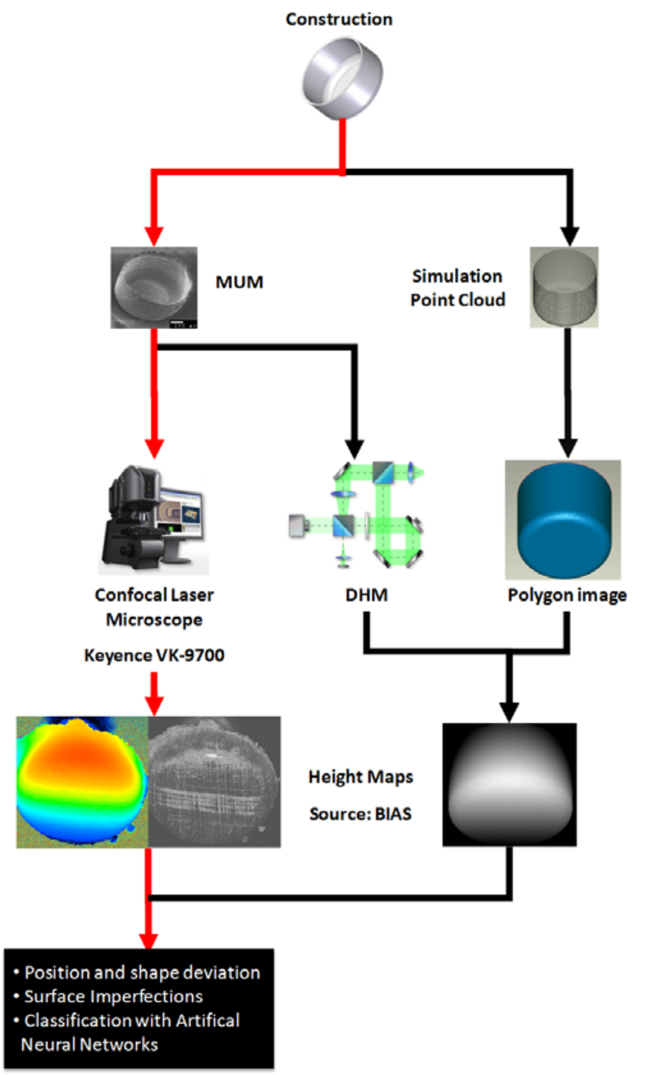


Figure 4: Micro-cup Evaluation Architecture

Detecting these manufacturing failures requires the use of robust and flexible machine vision techniques. Especially the high production rates of deep drawing processes with more than 1 million parts per week require very fast surface inspection routines in order to fit the cycle times. For this reason, the digital holographic microscopy (DHM) as a holographic interferometric metrology is intended to be used in-line, but is not yet completely installed. At the moment, confocal laser scanning microscopy is applied off-line but also delivers high-resolution images with depth selectivity. Thereby, the reconstruction of topologically complex objects is possible and similar to the expected height maps of the DHM.

3.1 Micro Deep Drawing

The investigated cup was manufacturing by a micro deep drawing process. This process is defined as the forming of a sheet metal part using pressure, so that a hollow is created, which is one-sided open. A stamp is mostly used for this purpose. Micro-cups or sleeves with a diameter of one millimetre or smaller can be produced by micro deep drawing.

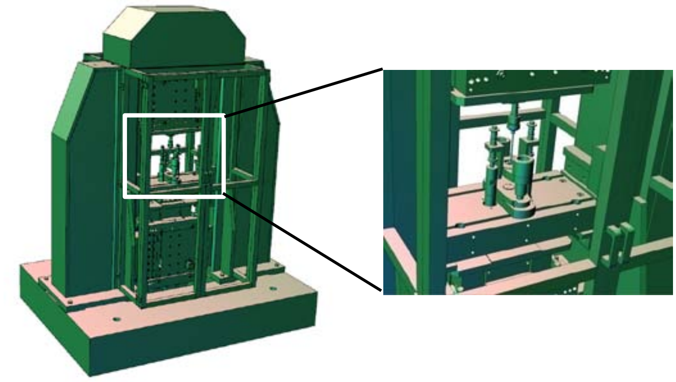
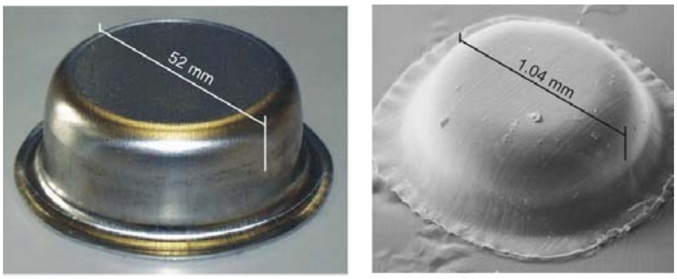


Figure 5: Micro forming machine (BIAS)

The diameter is about 1 millimetre with a sheet thickness of about 20 microns [21]. In comparison to macro deep-drawing, there are still small crinkles on the flange of the micro-part. Figure 6 compares the manufacturing between a macro- and a micro-cup.



Material:	Al 99.5	Al 99.5
Blank thickness:	1.0 mm	0.02 mm
Drawing ratio:	1.8	1.8
Punch diameter:	50 mm	1.0 mm
Drawing depth:	25 mm	0.5 mm
Drawing velocity:	25 mm/s	1.0 mm/s

Figure 5: Comparison of micro and macro deep drawing cups [21].

The drawing velocity of the micro-cup is 1.0 mm/s. The realisation of bulk production requires an automated measurement system in order to identify the small surface defects. Afterwards, a classification system is necessary to classify the defects. The two most common possible surface defects are shown in Figure 6. On the left image is shown wrinkling and on the right image you can see fracture of the micro-cup. For example, the wrinkling mode occurs because the hold-down force, which is applied to the pressure plate or blank holder, is inadequate [22].

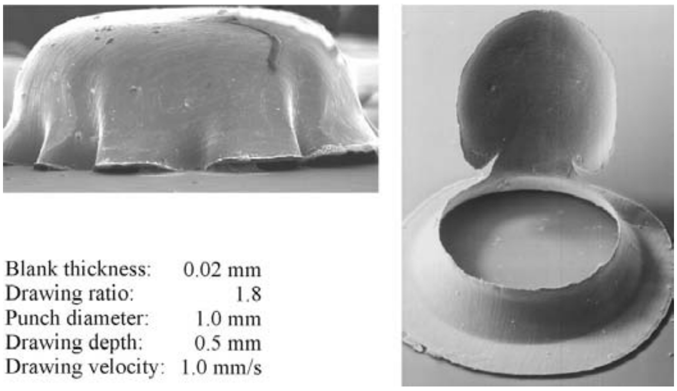


Figure 6: Failures of micro deep drawn cups [21].

3.2 Confocal laser microscopy

The great advantage of a confocal laser scanning microscope to a conventional microscope is the rejection of the light that does not come from the focal plane. This enables optical slicing and construction of high resolution three dimensional images. Further its high axial resolution, sharp image quality and associated quantitative image analysis provides structural information in the mesoscopic range for the full three dimensional realisation of the microstructure. Consequently, the same micro component can be subjected to multiple investigations either in a time series or with different geometrical orientations [20]. Figure 7 shows the working principle of a confocal laser scanning microscope.

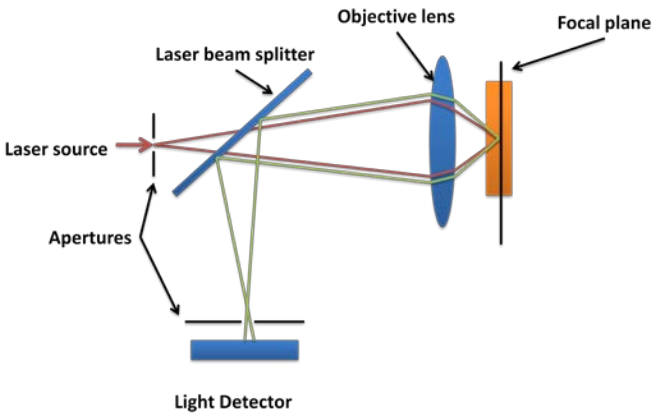


Figure 7: Working Principle of a confocal laser microscope [20].

For mapping the surface of the micro-cup the Keyence VK-9700 confocal laser microscope was used. The wavelength of the laser unit is in the violet range at 408 nm. The other technical data of the microscope is shown in table 1. The described measurement range is the minimal field of view. The complete measurement range in vertical direction is up to 7 mm.

Number of pixel	2048x1536 pixel
Measurement range (vertical)	67 µm (highest enlargement)
Resolution	0.001 micron
Repeat accuracy	0.02 micron
Optical zoom	1x to 6x
Light-receiving element	Photoelectron Multiplier Tube

Table 1: Technical Data Keyence VK-9700 [23].

3.3 Height maps

The result of the laser scanning is an high resolution height map, in which the surface structure of the object is described. The height map is a raster image, which represents the surface elevation of the analyzed object in 3D. The pixel information represents the distance from the laser unit to the micro object. Therefore, the map can be used for the evaluation of the surface.

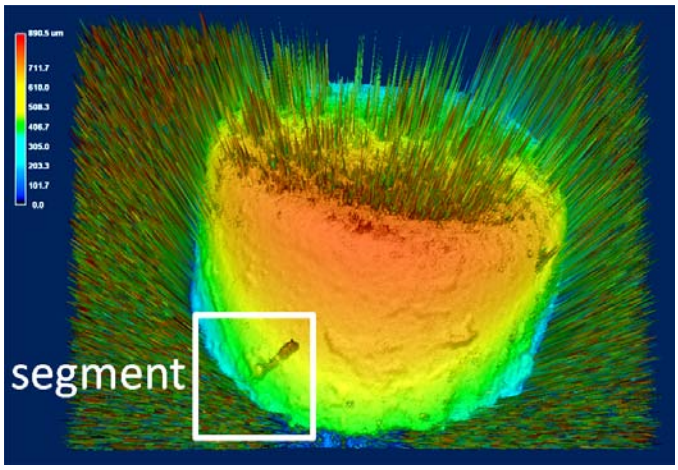


Figure 8: Height map of the micro-cup back.

Figure 8 illustrates a height map of a micro-cup. The cup is embedded in a noisy environment. The brightest part of the object displays the nearest part of the object to the laser unit. Above this area, the upper side of the cup is visible. Due to the scanning angle of the micro-cup, this area is as well influenced by measurement noise. The marked segment in Figure 8 displays a manufacturing error. In this case, a wrinkle exists on the surface. To detect this manufacturing error automatically, classical image processing methods are applied.

3.4 Image processing

In order to detect surface defects of the micro-cup, several classical image processing methods are applied. Figure 9 illustrates the sequence of the different image processing steps. After the image has been acquired using the confocal laser microscope, pre-processing algorithms are executed to remove insignificant information from the height map.

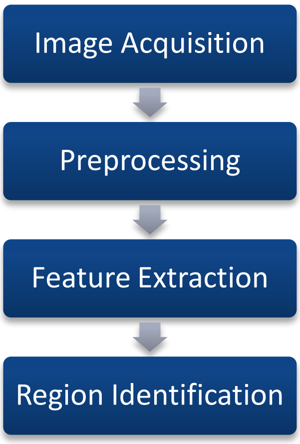


Figure 9: Image Processing Steps

Afterwards, relevant characteristics occurring in the image, e.g. abrupt changes in the pixel values are extracted. Finally, feature regions are identified in the image, which contain the determined characteristics and satisfy particular conditions.

3.4.1 Image acquisition and segmentation

To choose the relevant parts and to ensure efficient processing, the image is segmented into smaller areas. Figure 10 shows the height map of the segmented area, which is marked in Figure 8 and contains the wrinkle.

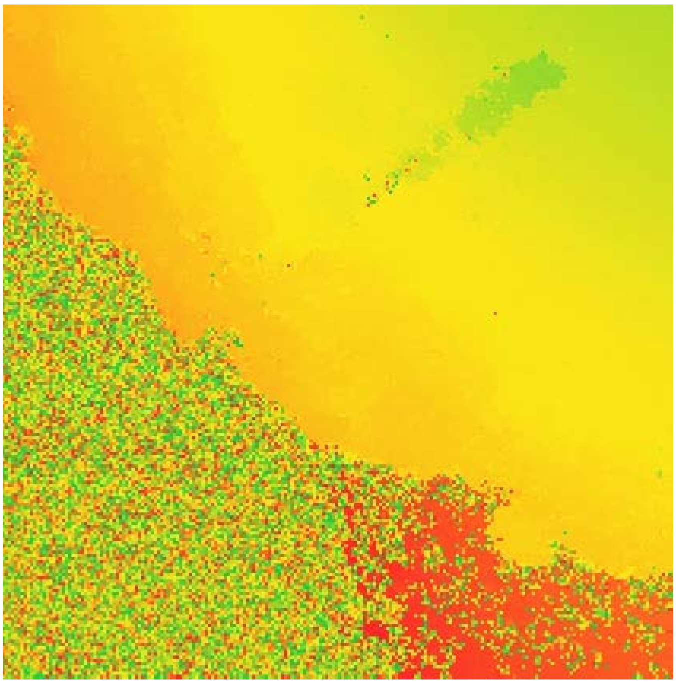


Figure 10: Segmented area of the height map with a surface defect.

3.4.2 Preprocessing

Processing the whole image is inefficient, since a large area of the height map represents non-relevant background information, which exhibits measurement noise of the laser unit. To distinguish between object and background neighbourhood operations are used. In the first step, the standard deviation of the average value of each pixel's neighbourhood is computed. Here, neighbourhood patterns are expressed as 20x20 matrices. For example, figure 11 shows a simplified 3x3 neighbourhood pattern. In this case, pixel P at row x and column y in the image has eight neighbours N.

N (x-1,y-1)	N (x,y-1)	N (x+1,y-1)
N (x-1,y)	**P (x,y)**	N (x+1,y)
N (x-1,y+1)	N (x,y+1)	N (x+1,y+1)

Figure 11: Neighbourhood Pattern 3x3

The standard deviation from the average value of the pattern is computed and stored at position (x,y) of a new result matrix. This operation is executed for each pixel in the height map. The new matrix finally contains information about the distinction between micro object and image background. A pixel that contains noisy background information is thereby characterized by a high deviation. In contrast, pixels which are part of the investigated micro object are characterized by a small pixel value. The distinction, if a pixel is assigned to the object is done by a threshold value. Thereby, a separation between object and background is accomplished. Currently, defining the threshold value is done by hand. In the future, we plan to determine the threshold of each image automatically by employing Ridler and Calvard's method [24].

The identified object area is still affected by measurement noise. To decrease the influence of the noise, a median filter is used. By applying this non-linear filter algorithm, the influence of the measurement noise is reduced without edge smoothing. The working principle is similar to the computation of the standard deviation. The neighbourhood pattern is applied and the median of the pattern is computed. For processing speed reasons the filter is only applied to the image regions which are recognized as object areas in new matrix. The result of the filter operations describe a mapping of the surface structure, which is illustrated in Figure 12. The red area represents a sector where high surface differences are situated. In this case, it represents the area of the measurement noise. The green section represents the area of small height differences. Attention should be paid to the size of the relevant neighbourhood of a pixel. Choosing a small neighbourhood can generate a low mean deviation when the neighbourhood of the pixel is smaller than the dimension of the cavity in the surface. In this case, the inner part of the cavity would not be classified as a part of the surface defect.

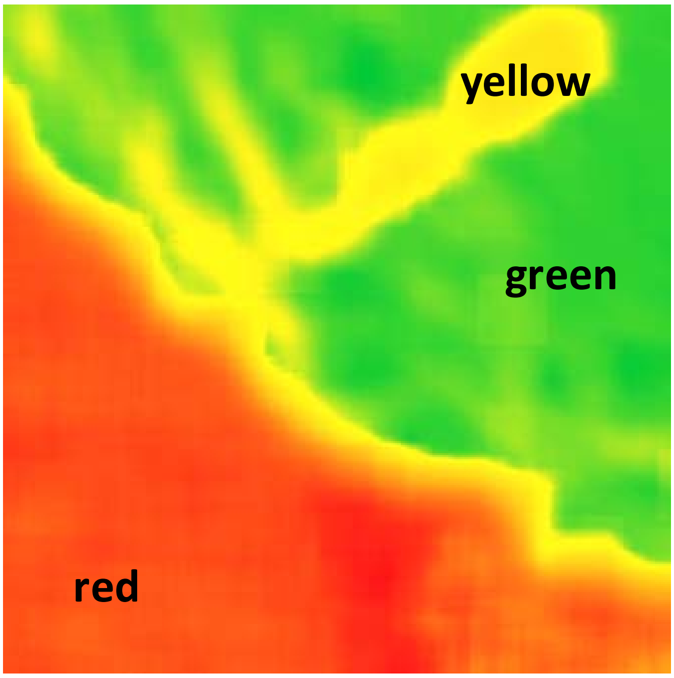


Figure 12: Profile of mean deviations as detection for noise.

On the other hand, a very large neighbourhood environment can lead to omission of surface errors as the pixel area of the defect may not be big enough and could be filtered out of the image.

3.4.3 Feature Extraction

Surface defects like cavities, blisters or wrinkles are characterized by an abrupt change of the pixel values in the height map. These changes are mostly characterized by an edge on the surface of the micro-cup. An edge represents a possible surface defect, when the difference in the pixel values between the edge and the surrounding object surface exceeds a specific value. Additionally, the shape of the edge has to be connected. Single edges, which are not connected, can represent cracks or scratches. The focus of our implementation is to identify wrinkles and open cavities on the surface of the micro component. The objective of the following steps is to extend the prototypical implementation with the ability to detect and classify scratches and cracks.

In order to identify edges on the surface, several edge detecting algorithms exist, e.g. the Sobel-Operator, Prewitt Operator and Canny Algorithm [25]. These methods detect high differences between the single pixels and emphasize edges in the image.

3.4.4 Region Identification

After detecting the edges on the surface, possible defect regions have to be determined. A connected edge represents a defect region when the embedded area has a particular size and the change of the pixel values between the edge and the surrounding area exceeds a predefined threshold. The size and shape of the region and the values of the containing pixels are input parameters for the following classification step conducted using artificial neural networks, because they are suitable for identifying cracks on surfaces on the basis of machine vision [26].

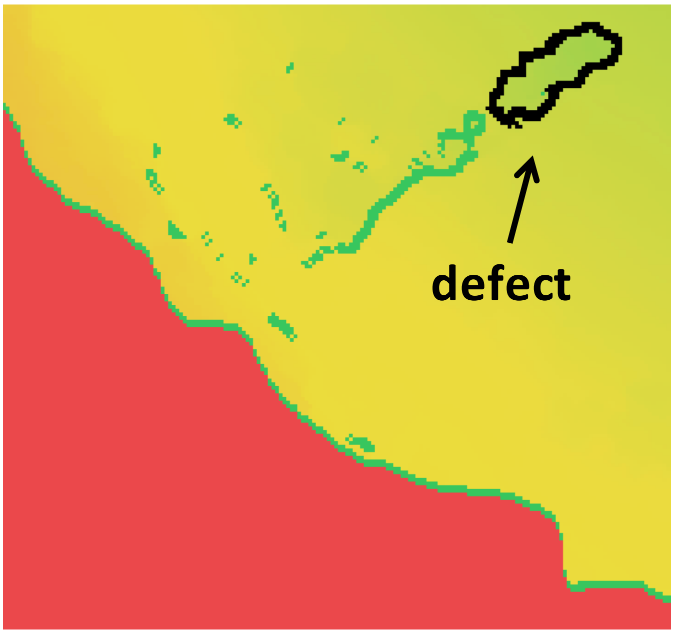


Figure 13: Defects at the surface of the micro object.

Figure 13 illustrates the investigated image segment with possible defect regions, which are marked as black areas. These regions are analyzed and evaluated in the following defect classification step. To enable faster and better pattern recognition we use standardized 7x7 pixel-matrices. Using only 49 Pixels makes it easier for the classification method to learn different types of surface defects. More pixels would allow a finer classification, but we don’t need this at the moment. Also the teaching would require more training data. Because of this, we scale down the defect areas to 7x7 pixel. The longest side of the defect reaches from bottom left to top right.

3.4 Classification Concept

The exact classification of material surface defects is an essential part of the intended micro quality assurance system of the CRC 747. The fast and efficient classification should support the technical engineers in the task of process configuration. As mentioned before, besides the low degree of automation the process configuration is the most costly part in micro production. Therefore the test runs for the process parameter adjustment should be evaluated by the machine vision system with only few samples.

The feasibility of an automatic surface defect classification system was evaluated by means of 100 synthetical defect images, each of which a standardised 7x7 pixel matrix was extracted from, serving as a feature vector for classifier input. These matrices were then annotated with ground truth classes manually. A total of five classes were used: crack, groove, dent, raising and blister. Based on the annotated dataset a classifier shall be trained to correctly identify the kind of error shown on an input image with best possible performance.

In our application, the performance exhibited by a specific classifier can be expressed as the percentage of correctly classified images. However, we are not interested in how well a given classifier is able to reflect the training data. This value may in fact be well too high due to overfitting. Instead, we seek to estimate recognition rates for new data, yet unseen by the classifier. There are different approaches as to performing such estimation. When enough data is available we may split the dataset into two disjoint subsets, named the training set and the test set. The training set is then used for training the classifier whereas the test set is used to estimate classification performance on unseen data. Unfortunately, this approach comes with a considerable disadvantage: since the classifier is not trained on the test dataset, potentially useful training data is omitted. That is, a classifier with better performance may be realized by training it on the complete dataset. This issue usually poses a problem especially when working with small datasets like our 100 samples.

In order to solve this problem and still guarantee an independent estimation of error-rates exhibited by a certain classifier, we employ cross validation. Here, the available dataset is broken up into n subsets. Then n-1 subsets are used for training and the remaining part of the data is used for testing. This process is repeated n times, thus ensuring that each subset is used once for testing. In this particular work, we employ a special form of cross validation where n equals the number of records in the complete dataset. The so-called leave-one-out-cross-validation removes one record from the dataset in each run, whereas the remaining ones are then used for training. Finally a test is performed on the removed record. In order to estimate the classifier's performance over the full dataset, this process is repeated until every record in the data has been withheld once.

To perform the classification experiments we employ the Weka Data Mining open source software, which provides implementations of numerous machine learning approaches [27]. We examined the C4.5 algorithm as a solution for automatically generating decision trees (labelled J48 in Weka), Naïve Bayes as a probabilistic approach, and, a multi-layer perceptron as an implementation of an artificial neural network. Tests performed by utilizing the previously described leave-one-out-cross-validation resulted in a recognition rate of 94% for both the decision tree and Naïve Bayes. The neural network performed slightly better, exhibiting a recognition rate of 95%. Concluding, we could identify the decision tree approach as being especially suited in this particular case, because of its good recognition rate and the transparency of its results. That is, based on the decision tree itself it is possible to intuitively comprehend how decisions are actually made, which is simply impossible for the conditional probabilities of the Naïve Bayes or the abstract connection weights of the neural network.

4 Conclusion

The quality evaluation in micro production is challenging, because the manufacturing process has low tolerances and requires high accuracy. In order to detect surface defects on the micro-parts during the fabrication process, the digital holography microscopy is intended to record high-resolution height maps. These images allow the three-dimensional reconstructions of topologically-complex objects. The characteristics of micro production expose special needs for the surface inspection. On the one hand, we have to deal with very small tolerances which acquire an adaptive adjustment of thresholds. On the other hand, we have to face handling problems of micro-parts, which do not allow an exact positioning and requires an adaptive machine vision technique.

This paper shows the application of classical image processing techniques, like filtering, segmentation and neighbourhood methods in order to identify height map areas, where possible surface defects are situated. First implementations of our approach show the general success of filtering out defected surface areas. The following classification of the area is intended to be performed by an artificial neural network, which is initially trained with backpropagation algorithms. The training data contains different types of defect information like type and size of the defect. The objective of the next development steps is the complete implementation of the presented concept to detect surface defects at the analyzed micro-parts.

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