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Automatic design of classification systems for visual quality control of metallic surface

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Abstract – **In this paper we propose a new method for the automatic design of classification systems for the visual inspection of metallic surfaces. Feature selection and selection of a suitable classifier as well as its optimization are done fully automatically on the base of a set of representative images for all quality respective defective classes to distinguish. Texture and colour features, which are most suitable for discrimination between different quality classes, are also explained. Furthermore, we present a flexible software architecture based on Windows Workflow Foundation and Windows Communication Foundation for the separation of image acquisition and classification. With this scheme a process architecture with many thin clients for image acquisition and one high-capacity evaluation system can be built up.**

I.   INTRODUCTION

The quality assurance is a crucial step in the process of machining metal parts. Functional aspects, e.g. tribological properties or surface parameters in sense of profile or areal roughness characteristics as well as aesthetic aspects are important. These parameters are mostly registered with expensive 3-D measurement systems. It turns out that many defects can also be recognized in 2-D images, which can be captured with relatively cheap and robust systems also inside of the metal-cutting machine. Image processing and machine learning algorithms can be used for an automatic image based classification. The problem arises with the very complex step of designing the classifier system. This limits the applicability of such systems especially for small and middle-sized companies and production lines. With our proposed method (fig. 1) it is possible to design a classification system fully automatically based on a set of 50 till 250 representative images of objects from the classes to discriminate between. Furthermore, only the setup of the illumination and image acquisition system needs to be done by the application engineer. For this design step different supplier like [1] and [2] offer knowledge and support in form of technical questionnaires and decision support systems as well as expert guidance. In [3] a machine integrable 2-D measurement for metallic surfaces is presented. The system has an HSK-interface and wireless GigEVision support and thus is suitable for image capturing inside machines.
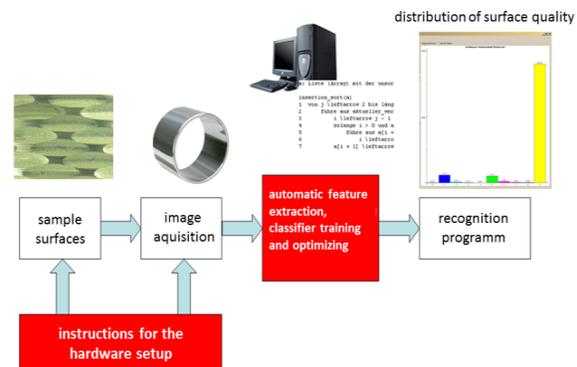

Fig. 1. Scheme for automatic classifier model design

We have proved the applicability of our proposed scheme on a dataset with three quality classes (fig. 2) and 274 sample images, which were aggregated into two classes: good parts (Perfect Surface) and bad parts (Longitudinal Rills and Chatter Marks).

Class Name	Example Image
Longitudinal Rills	
Perfect Surface	
Chatter Marks	

Fig. 2. Investigated dataset with three quality classes of metallic surfaces

II. IMAGE FEATURES AND AUTOMATIC FEATURE SELECTION FOR VISUAL QUALITY CONTROL OF METALLIC SURFACE

Surface defects are influencing the local reflection characteristics. This appears as changes in brightness and colour in the 2-D-image. Colour features are mostly suitable for the recognition of surface defects on coated surfaces and composite materials. Texture features are optimal for recognition of surface defects on chipped metallic surfaces. Different texture images can be calculated from the intensity channel of the raw image. We propose the following filter-based texture features: Absolute Central Moment (ACMO), BREN (Brenner gradient), CONT (Image contrast), CURV (Image Curvature), TENV (Tenengrad variance), VOLA (Vollath's correlation), GRAE (Energy of gradient), GRAT (Thresholded gradient), SFRQ (Spatial frequency), SFIL (Steerable filters). [4], [5] From texture images arithmetic mean and standard deviation are calculated, which serve as features for classification.
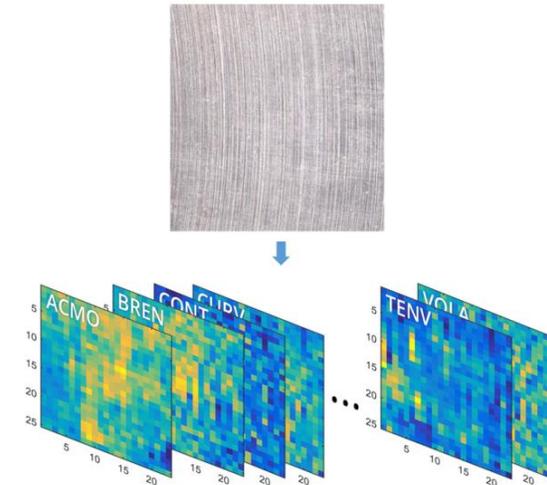

Fig. 3. Raw surface image and its texture images

Table 1. Correlation 3-D and 2-D features

3-D Parameter	description	correlation with
S_a	arithmetic average of absolute surface height values	ACMO
S_q	root mean squared of the surface height values	GRAT
S_v	maximum valley depth	SFRQ

The correlation between established 3-D parameters and the 2-D texture parameters was investigated. It turned out that three different parameters show a strong linear correlation with correlation coefficient r = 0.8. These parameters are shown in table 1.

Beyond these complex filter-based texture features more simple colour and texture features in the HSI colour space were examined. These were mostly arithmetic mean and deviation of gray values in the HSI colour space, features from the gray level co-occurrence matrix (e.g. entropy, correlation) and moments from the gray plane. This resulted in totally 200 image features, which were evaluated with the well-known ReliefF [6]. The distribution of the ReliefF-Score on the training dataset is shown on figure 4.
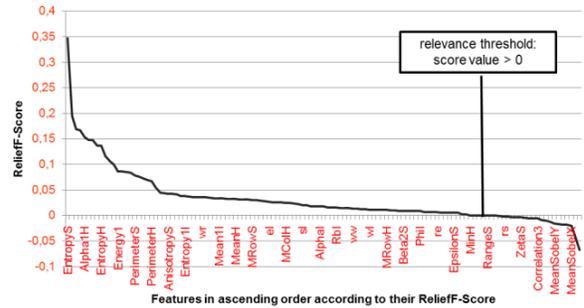

Fig. 4. Distribution of ReliefF-Score

The ReliefF-Score has the great advantage that a suitable relevance threshold can be determined. Every feature with a relevance score below 0 is not relevant and thus can be eliminated from the feature vector. This forms the basis for the automated feature selection.

III. CLASSIFIERS AND AUTOMATIC CLASSIFIER SELECTION FOR VISUAL QUALITY CONTROL OF METALLIC SURFACE

After the Calculation of positively evaluated features, we estimated the recognition rate of different supervised classifiers by means of 10-fold cross validation:

- random separation of the sample into 10 sub-samples,
- separation of one sub-sample as test portion, rest for training portion ,
- calculation of the number of correctly classified instances,
- repeating the procedure for every sub-sample and
- calculation of the average recognition rate.

We have chosen the simple classifier Naïve Bayes and K-nearest neighbour, the more complex decision tree J.48 and RandomForest as well as the complex support vector machine according to our research within the field of machine learning (published e.g. in [7], [8], [9]). The results are shown in table 2. Naïve Bayes and K-nearest neighbour are only suitable for simple recognition

problems, J.48 is suitable for recognition problems with low and middle complexity (similar behaviour shown in former research on other recognition tasks 10], [11]). The support vector machine (SVM) and RandomForest are suitable for simple up to complex recognition problems. The primary 2-class-algorithm of SVM can be extended to multi-class problems. The crucial step is the optimization of the complexity parameter (Nu for Nu-SVM and C for C-SVM) and the kernel parameter. The Nu-SVM, proposed by Schoelkopf et al uses a parameter Nu for controlling the number of support vectors [12]. The parameter C in the ordinary SVM can take any positive value, Nu is bounded by 0 and 1. The results from our sample dataset indicates that the polynomial kernel is mostly suitable. But for more complex data the rbf-kernel is more convenient. The kernel is defined:

$$k(x, x_i) = e^{-\gamma \|x - x_i\|^2}$$
$$x - Feature - Vector$$
$$x_i - Support - Vectors \qquad (1)$$
$$\gamma - Gamma$$

The parameter Gamma can control the complexity and thus the classifier can be optimally adapted to datasets of any complexity. This can be done with multi-dimensional optimization algorithms. Because of the bounds on the complexity parameter the Nu-SVM is more suitable for automated optimization. The training vectors on the class boarders are called support vectors.

Table 2. Classification Results with different Classifiers

classification algorithm	10 times 10-fold cross validation	10 times Split 66%
Naïve Bayes	65.33% (Std. 8.65)	67.24% (Std. 2.89)
K-nearest neighbour	88.94% (Std. 5.05)	86.35% (Std. 2.85)
J.48	86.61% (Std. 7.47)	81.85% (Std. 5.17)
RandomForest	94.09% (Std. 4.37)	93.88% (Std. 2.32)
SVM+ PatternSearch	99.26% (Std. 1.66)	99.14% (Std. 0.45)
SVM+ GridSearch	99.56% (Std. 1.31)	99.46% (Std. 0.56)

The optimization principle based on calculation of the recognition rate for different equidistant (Nu, Gamma)-pairs (fig. 5). We get a 2-dimensional function:

$$Recognition\ Rate = f(Nu/Cost, Gamma) \qquad (2)$$

We tested the following optimization algorithms: Nelder-Mead, Interior-Point, Active-Set, Sequential Quadratic Programmierung, Quasi-Newton, Pattern Search, GridSearch, Genetic Algorithm, Simulated Annealing. Now GridSearch and PatternSearch algorithms can be used to find the maximum of recognition rate.
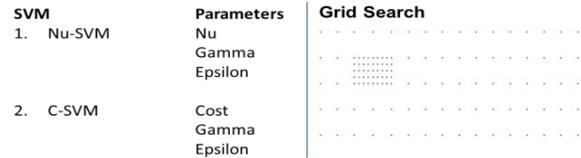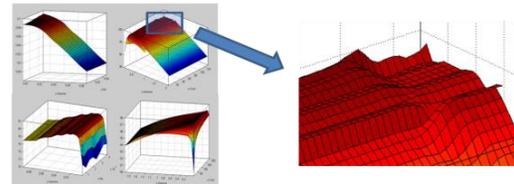

Fig. 5. Recognition Rate as function of Nu/Cost; Gamma

Our experiments indicated that GridSearch is able to find the optimal parameter pair. PatternSearch is four times faster than GridSearch but its results are sensible to the chosen starting point. We can cope with this problem by applying an one-dimensional search for a sub-optimal gamma under constant small Nu.

IV. FLEXIBLE SOFTWARE ARCHITECTURE OF CLASSIFICATION SYSTEMS SUITABLE FOR SMART FACTORIES

The above described steps for automatic design of classification systems were implemented in a software architecture consisting of two parts:

1. Windows Workflow Application for classifier model design (training stage)

Input: sample images with class information
Output: serialized array with indices of relevant features (feature indices) and classifier model

2. Class library for object recognition (classification stage)

Input: classifier model, feature indices, camera parameters, image to classify
Output: estimated class

For image acquisition we use the uEye camera family from the manufacturer IDS imaging [13]. The camera is parametrized with an application from the manufacturer. The parameters are stored in an INI-file and loaded from the recognition program. Our class library (fig. 6) can be integrated in every .NET-based program. Image acquisition and classification can be separated into two processes. So we can use a thin client like cheap and well-known Raspberry Pi [14]. The classification can be executed on a powerful evaluation system because all classes are communicating via fast NetTcp-Bindings by use of Windows Communication Foundation (WCF).
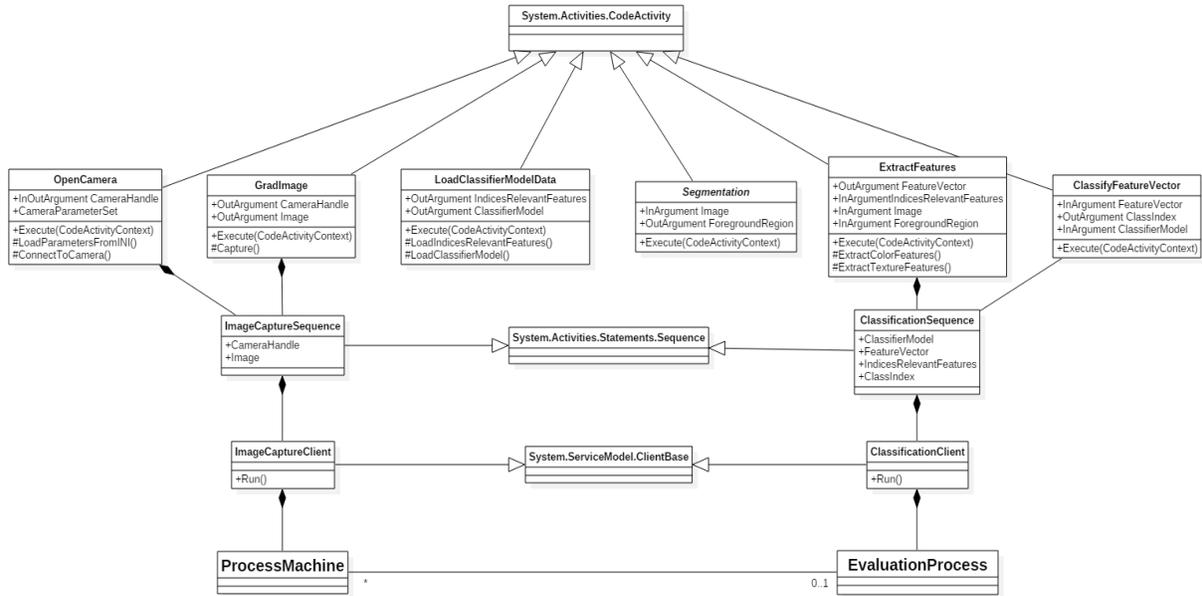
Fig. 6. UML-diagram of class library for automatic classifier design

In the field of surface defect recognition we often observe a small field of view with high optical magnification. As a result of this, we often do not need segmentation. An opposite example is shown in figure 7. We want to analyse the flanks on the counter sink. Thus a segmentation step is necessary to eliminate background regions. This step is highly depending on the application. So our segmentation class is abstract and conducted for implementation by the application engineer.
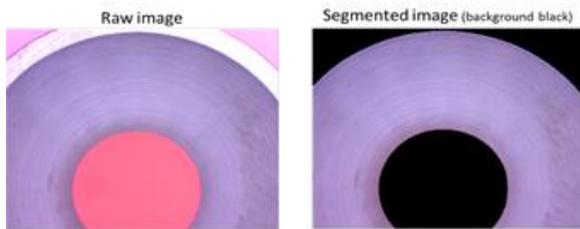

Fig.7. Segmentation on counter sink

V. CONCLUSION

The proposed scheme can be used for flexible design of image-based recognition systems consisting of automated feature selection and classifier optimization. A possible software implementation was presented. We have tested the system for defect recognition on metallic surfaces. We reached recognition rates of about 99%. Further tests on other applications, for example defect recognition on composite material are planned for the near future.

VI. ACKNOWLEDGEMENTS

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