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AUTOMATIC PETROGRAPHIC INSPECTION BY USING IMAGE PROCESSING AND MACHINE LEARNING

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Abstract: In this paper we present a method for an automatic inspection of mineral aggregates. Certain components of aggregates can negatively affect the mechanical strength of produced concrete or asphalt as well as cause the destructive alkali silica reaction. The automatic recognition of such aggregates could be successfully implemented by means of image processing and machine learning algorithms. We achieved a total recognition rate of 88% for this very complex recognition problem. Therefore every step in the pattern recognition process has been successfully optimized. In conjunction with the object singularization we achieved a fully automatic testing instrument for petrographic inspection.

Keywords: aggregate, petrographic inspection, SVM, machine learning

1. INTRODUCTION

Mineral aggregates which are used as concrete or asphalt additives must be analyzed according to certain European standards, in Germany also according to relevant federal standards, for example [1] in Saxony-Anhalt. Samples from natural mineral deposits need to be taken at frequent intervals for the analysis of pebble components. Two cases illustrate the importance of this analysis: In the federal state Hessen in Germany nearly 350 km of the expressway made of concrete are affected by the well-known alkali silica reaction (ACR) [2]. The Rammrath bridge over the Teltow-channel in Germany needs to be demolished and buildt up newly after only 34 years also caused by alkali-silica reaction. This is very harmful and cost-intensive. Another problem is that specific pebble components can negatively affect the mechanical strength of the produced concrete/asphalt.

The state of the art for analyzing mineral aggregates is a manual inspection by specific trained experts (like a mineralogist or geologist). This procedure is time-consuming, error-prone and depends on the individual experience of the inspector. Automatic routines can only be found for the analysis of few specific mineral components (for example Calcite and Dolomite) by using the NIR spectra [3]. But the given mineral aggregates, which are used as concrete or asphalt additives, are mixed mineral components. So the determination by using NIR-features is more difficult than the separation of pure minerals. Wotruba et al. wrote that the number of minerals, which can be automatically analyzed in NIR, is limited because not all minerals showing diagnostic absorption features and very dark minerals can also cause problems by absorbing a high amount of the electromagnetic spectra [3]. The image analysis of grinding surface patterns is another way for automatic classifying of mineral aggregates [4]. This procedure is used for the inspection of grinding surface patterns of mineral plates. This procedure needs a costly mechanical processing of the mineral surface. This is not useful for the classification of mineral aggregates as untreated stone material.

This paper describes an automatic routine for petrographic inspection by using image processing and machine learning algorithms in the visible spectrum (VIS). We have implemented an automatic recognition method to analyze pebble components of an aggregate sample with a weight of nearly 1 kg to overcome the ACR problems.

The whole algorithm is described according to the classical pattern recognition chain in Fig. 1.

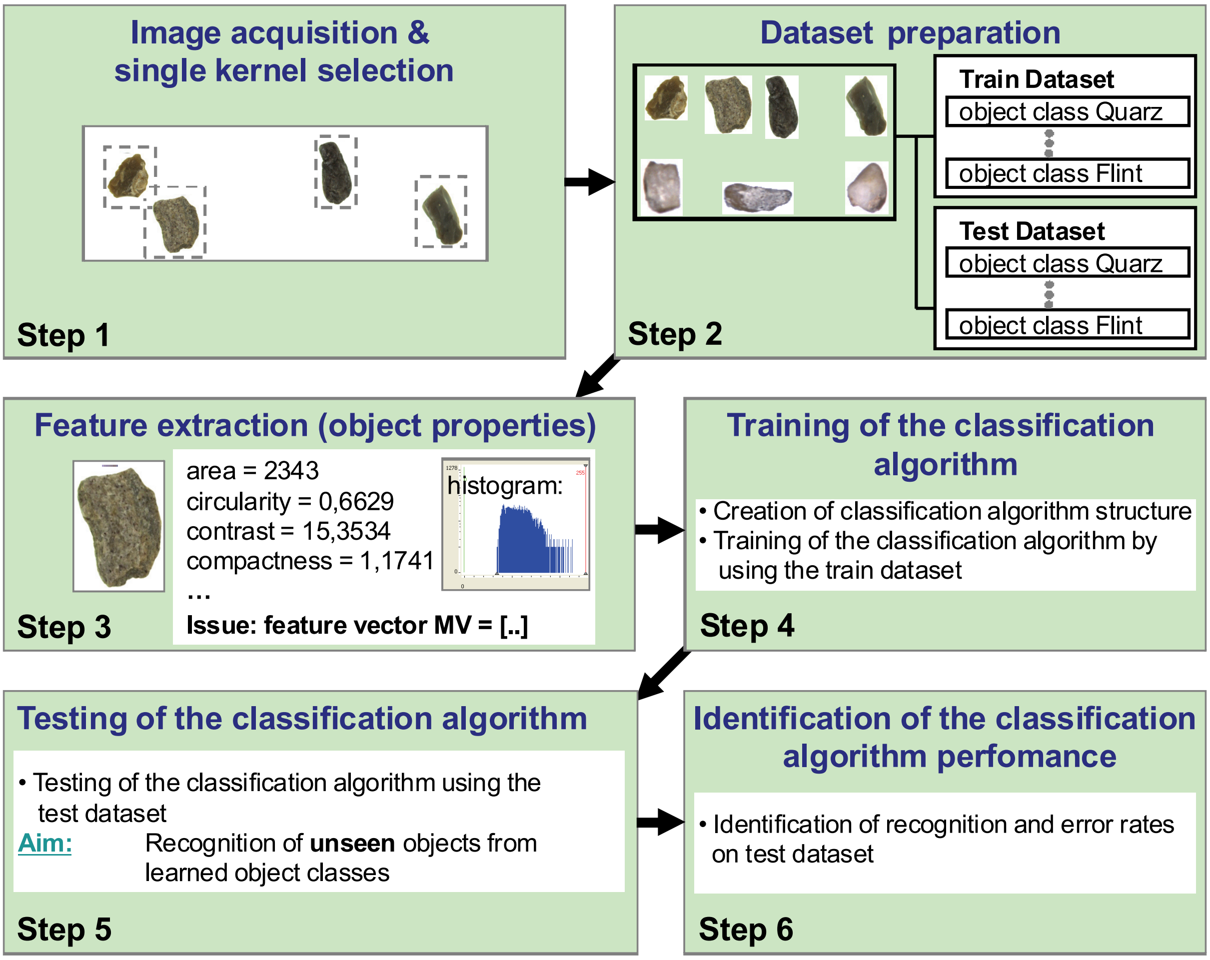

Fig. 1 Pattern recognition chain for petrographic inspection [5]

For classification we used the Support Vector Machine (SVM) which is considered one of the most powerful classification algorithms today in conjunction with useful image features.

2. IMAGE ACQUISITION

For this research in the field of image based recognition of pebble components a specialized system for feeding, separation and image acquisition was developed (Fig. 2). It is possible to handle the sample components sized from 4 till 32 mm in diameter with the developed device. The sample is filled in the charging bin, gets separated via a V-profiled chute and tracks over a belt conveyor. The aim is to get non-touching and non-overlapping objects in the field of view of the color line scan camera resulting in single object images after segmentation.

Two datasets were generated with different sample objects by using the described image acquisition device. Totally nearly 16,000 objects were given for building up a training dataset. This dataset was used to tune the SVM parameter via cross-validation. The final classifier model was trained on the whole training dataset. In addition an independent test dataset with nearly 3,000 objects was acquired. Both datasets were acquired on different days to cover also effects from a possible slightly unstable illumination. All images are stored in loose-less Windows-Bitmap-format (BMP). Some sample objects are shown at Fig. 3 and Fig. 4. The different pebble types could be combined to 4 superordinated classes (also termed groups).

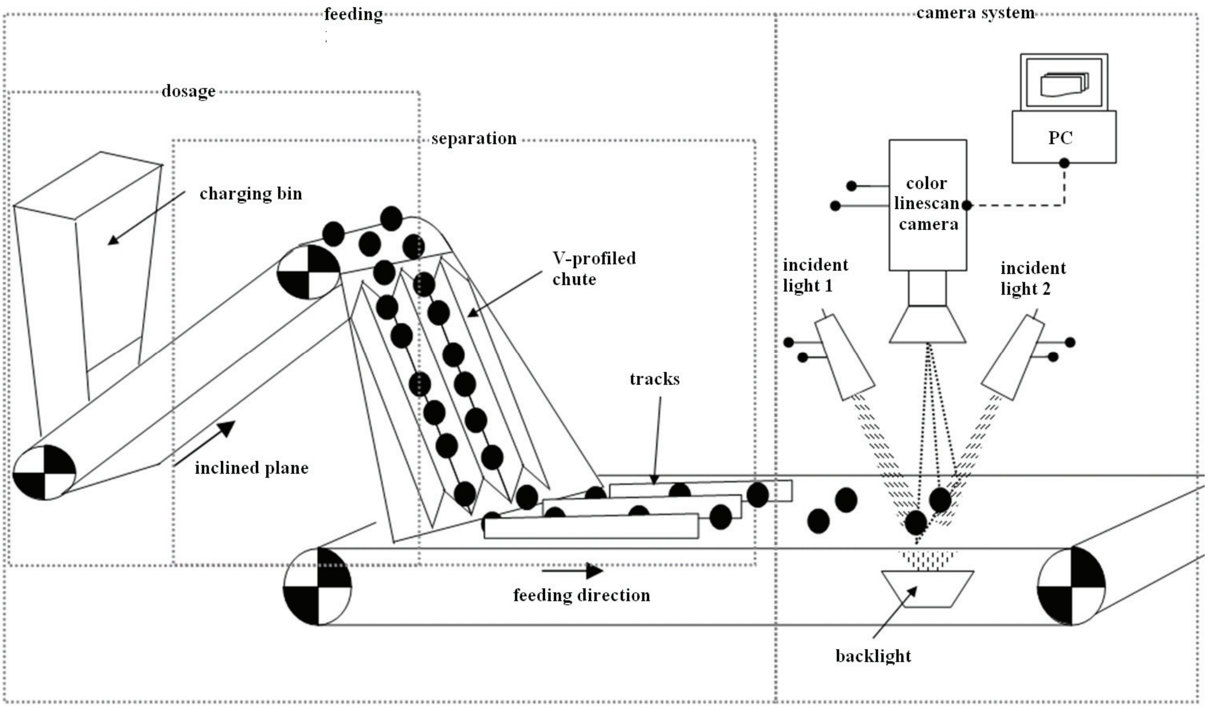

Fig. 2 Device for feeding, separation and image acquisition

Group 1 (Fig. 3) consists of harmless objects for production of concrete. The groups 2 and 3 (Fig. 4) are especially considered objects which should not be added to concrete because of the given risk of ACR.

The main problem is that some objects from different classes have a very similar physical appearance (Fig. 5). If you only want to estimate the superordinated group to which an object belongs, it doesn't matter for most of the combinations (for example rhyolite and granite both belong to group 1).

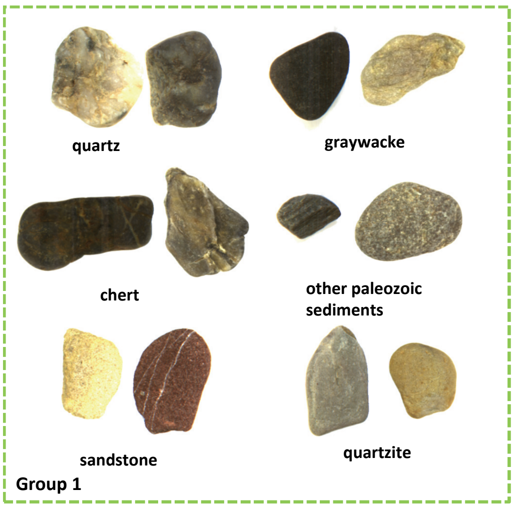

Fig. 3 Pebble components

On the other hand sandstone and friable sedimentary rocks belong to different superordinated groups. This is a problem of the recognition task in general, which is resulting from high variability of the contemplated natural objects and high similarity between several classes.

Fig. 4 Pebble components to be considered especially

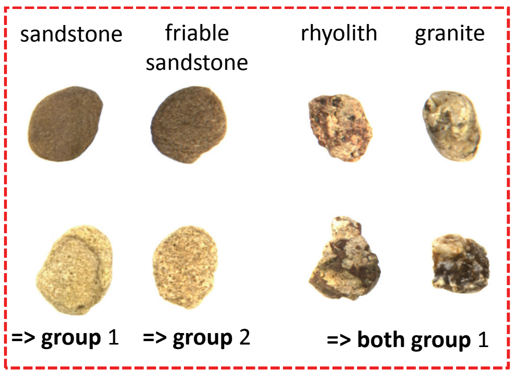

Fig. 5 Obviously very similar objects belonging to different pebble types

3. FEATURE EXTRACTION AND CLASSIFICATION

After an accurate segmentation of the foreground region the images was transformed from RGB to HSI colour space. In the next step a feature vector with 234 features (mainly colour and texture features) has been calculated. The used feature extraction algorithms are part of the machine vision software Halcon and were described in the release notes for MVTec HALCON 8.0.3 [6]. Exemplarily some color and texture features are described in the table below in a short way.

Table 1 Example for colour and texture features

Operator	Description
mean and variance gray (HSI)	mean and deviation of the gray values in the HSI colour space
co-occurrence matrix (I)	texture features calculated from the co-occurrence matrix
entropy (HSI)	entropy and anisotropy coefficient
fit surface first order (HSI)	approximates the gray values by a first order surface
intensity (HSI)	mean and variance of the gray values of the object region
min and max gray (HSI)	minimal and maximal gray value of the object region
moments gray plane (HSI)	approximates the gray values by a plane
plane deviation (HSI)	mean deviation from the calculated plane
Laws texture filter (HI)	mean and deviation of the hue and intensity channel filtered with 5x5 Laws texture filter

Experiments in feature selection were also conducted in the step of designing the final feature vector. We mainly used the information gain operator as described in [7]. It turned out that the most relevant features are gray value mean and deviation in the HSI colour space as well as entropy, anisotropy, features derived from the co-occurrence matrix and Laws texture features [8]. Entropy and anisotropy were calculated according to the following formulas:

$$entropy = -\sum_{0}^{255} rel[i] * ld(rel[i]) \tag{1}$$

$$anisotropy = \frac{\sum_{0}^{k} rel[i] * ld(rel[i])}{entropy} . \tag{2}$$

rel[i] is the value of the relative histogram for gray level *i*. The relative histogram is a histogram normalized in a way that the sum of all gray value frequencies is 1.

Also features from the well-known co-occurrence matrix (energy, correlation, homogeneity) seemed to be highly relevant. Another type of relevant features based on fitting planes to the gray values in the HSI colour space via least-squares-methods. The first order plane is described by:

$$J_1(n,m) = \alpha(n - n_{center}) + \beta(m - m_{center}) + \gamma. \tag{3}$$

with
n – row,
m – column.

The second order plan is given by:

$$\begin{aligned} J_2(n,m) = {} & \alpha(n - n_{center})^2 + \beta(m - m_{center})^2 + \\ & \gamma(n - n_{center})(m - m_{center}) + \\ & \delta(n - n_{center}) + \varepsilon(m - m_{center}) + \zeta . \end{aligned} \tag{4}$$

Both planes are described by their coefficients which serve as features for the classification process.
Furthermore the Laws texture filters were used to extract specific texture patterns. For this Laws filter kernels with size 5x5 are applied to the hue and intensity channel. The gray value mean and variance of the resulting images were utilized as features for classification.

4. PARAMETER OPTIMIZATION & ALGORITHM TEST

For the processing step of classification the work is focussed on the Support Vector Machine (SVM). The SVM was designed to solve binary classification problems. Many research has been done to expand the algorithm to multi-class problems [9],[10]. Our research indicates significant differences in classification accurency achieved by "one-versus-one" or "one-versus-all" strategies on the given problem (see Fig. 6). The major advantage of the SVM - especially in the field of recognition of highly variable natural material - is, that it maximizes the margin between the hyperplane and the closest training points on both sides. In this research the radial basis function kernel (rbf) was mainly used:

$$k(x, x') = e^{-Gamma\|x - x'\|^2} \tag{5}$$

The kernel parameter *Gamma* and the regularization parameter *Nu* of the SVM need to be chosen with care. To find an optimal parameter set a gridsearch method with 3-fold-crossvalidation was conducted on a training-set with nearly 16.000 objects (see Fig. 7). The performance of the classifier mostly depends on the value of *Gamma*. A higher *Gamma* results a higher impact of less relevant training samples on the decision boundary. The classifier learns the data at heart. The Parameter *Nu* can be considered as an upper bound for the training error and a lower bound for the amount of training vectors that become support vectors.

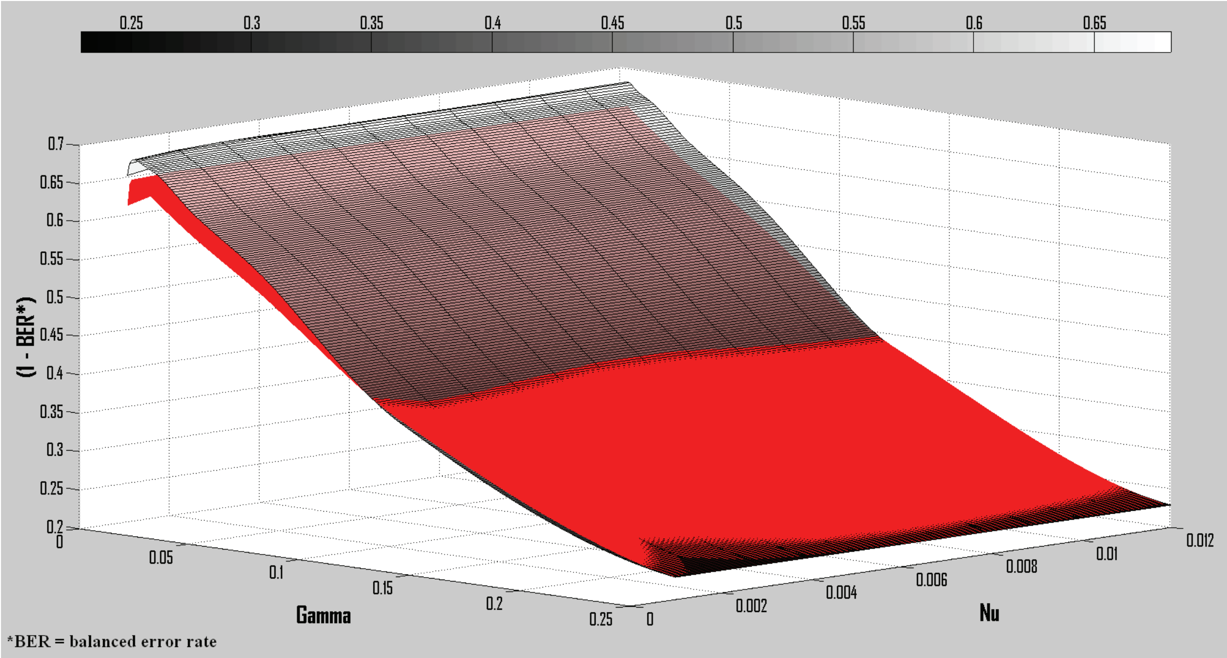

Fig. 6 Differences in accuracy between one-vs.-one (black surface) and one-vs.-all strategy (red surface)

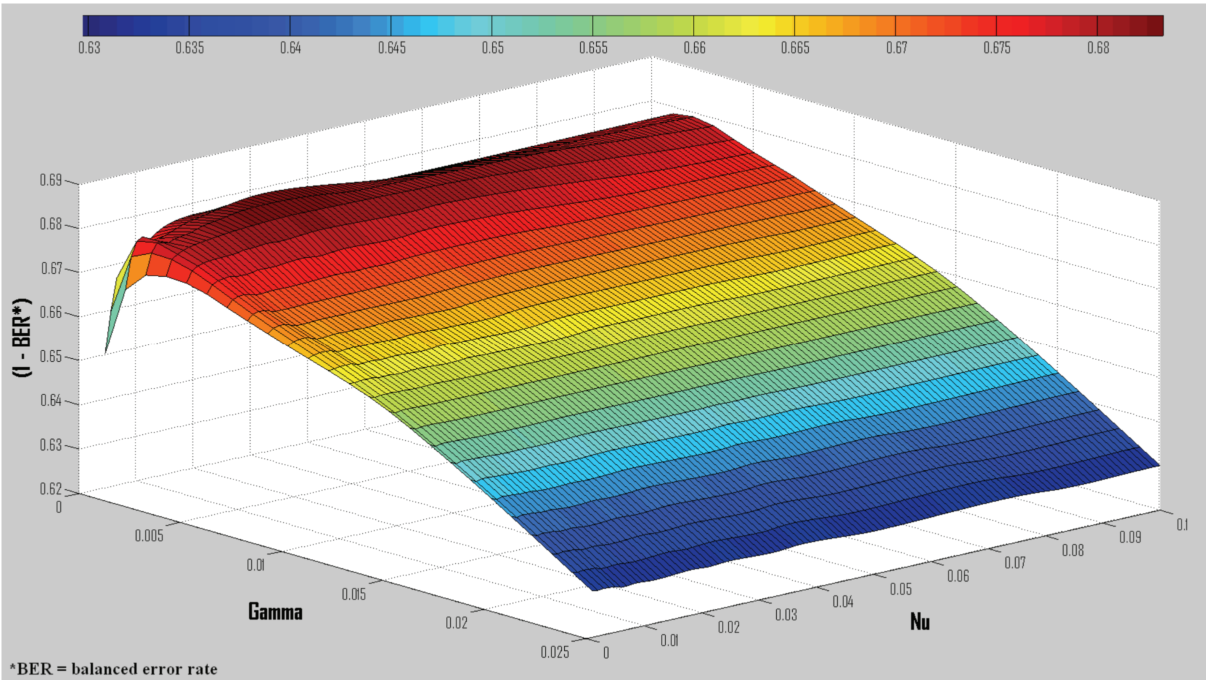

Fig. 7 Balanced error rate of the SVM depending on Nu and Gamma (one-vs.-one)

Table 2 confusion matrix of the final SVM model

		classified pebble category				Classification Performance [%]	
	real pebble category	∑ (1 - 10) Group 1	∑ (11, 12, 13) Group 2	∑(14) Group 3	∑(15,16) Group 4	recogni-tion rate per class	total recogni-tion rate
Group 1	1 quartz	**181**	3	0	2		
	2 chert	**221**	0	1	10		
	3 quartzite	**203**	14	0	4		
	4 graywacke	**155**	2	0	4		
	5 other paleozoic sediments	**192**	10	0	7		
	6 sandstone, siltstone, claystone	**171**	28	0	0		
	7 limestone	**198**	35	0	2		
	8 volcanic rocks	**184**	8	1	16		**88,1**
	9 basement rocks (e.g. granite, gneiss)	**193**	9	0	5		
	10 dense flint	**213**	5	0	21	**91,1**	
Group 2	11 porous flint	15	**72**	1	2		
	12 light and porous limestone and marlstone	21	**68**	0	0		
	13 friable sedimentary rocks	50	**98**	0	7	**71,3**	
Group 3	14 brown coal, xylit, carbonized wood	1	3	**39**	4	**83,0**	
Group 4	15 brown iron ore	13	7	2	**141**		
	16 pyrite, marcasite	6	0	1	**40**	**86,2**	

The position of the gridpoints in the intervall [0, $Max_{Nu,\ Gamma}$] are calculated according to the following formula:

$$Pos_{Nu,Gamma}(i) = Max_{Nu,Gamma} \cdot 2^{i-n+1} \qquad (6)$$

with $0 <= i <= 9$ and n=10

By this way 100 grid points (*Nu*, *Gamma*) were evaluated. The best parameter combination is chosen for the final classifier.

The balanced error rate was used, which is calculated as the average of the errors on each class, to get an undistorted estimation for the optimal parameters. The result is also affected by the number of objects in the test dataset for each class by using the normal error rate. Imbalanced data could be handled slightly better by using this method. The final test results achieved on an independent test dataset with nearly 3000 objects are shown on Table 2. According to the relevant version of the regulations for the inspection of pebble material used as concrete aggregate [1] the different pebble categories are combined into 4 relevant superordinated groups. According to past research results, e. g. [11] we have trained our classifier to differentiate between all 16 classes. Later the fusion in the four superordinated groups has been done on the level of the classification results. For example all objects classified as sub-class 1 (quartz) till sub-class 10 (dense flint) are labeled as superordinated group 1. So classification errors between the sub-classes within a superordinated group disappear. Furthermore more compact clusters could be reached in feature space.

With this final classifier model a total recognition rate of 88% was reached. By the analysis of the confusion matrix similar and underrepresented classes could be identified:

1. high mutual confusions argue for phenotypically very similar classes which are not clearly seperable in die visible domain,
2. high one-sided confusions argue for a under-represented class in the training dataset.

According to declaration 2 the training dataset should be modified and updated. By this way it should be possible to reach an accuracy higher than 90%. Declaration 1 has already been alleviated through the introduction of the 4 super-groups according to the valid standard for petrographic inspection.

5. CONCLUSIONS AND FUTURE WORK

In this paper a method to analyze pebble material was presented. A total recognition rate of 88% was achieved, which turned out to be a very good result for this complex task with very high intra-class-variability and low inter-class-variability. For future work we intend to use spectral imaging technology to analyze the material in the near infrared domain. First experiments indicate already promising results. In the next steps of our research a comparison between the results of the automated recognition system and the analysis done by a skilled geologist is also planned. As currently known this is the very first implementation of an fully automatic petrographic inspection according to the valid standards in Germany. Furthermore the used training dataset have to be updated with more sample objects, especially for underrepresented classes.

Further investigations and practical tests of the proposed method and the developed petrographic inspection system need to prove the applicability and robustness of the solution in practice.

6. ACKNOWLEDGEMENTS

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