Image Analysis in Tribodiagnostics

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Abstract
Image analysis of wear particles is a suitable support tool for detail analysis of engine, gear, hydraulic and industrial oils. It allows to obtain information not only of basic parameters of abrasion particles but also data that would be very difficult to obtain using classical ways of evaluation. Based on the analysis of morphological or image characteristics of particles, the progress of wearing the machine parts out can be followed and, as a result, possible breakdown of the engine can be prevented or the optimum period for changing the oil can be determined.

The aim of this paper is to explore the possibilities of using the image analysis combined with the method of analytical ferrography and suggest a tool for automated particle classification. Current methods of wear particle analysis are derived from the evaluation that does not offer an exact idea of processes that take place between the friction surfaces in the engine system. The work is based upon the method of analytical ferrography which allows to evaluate the state of the machine. The benefit of use of classifiers defined in this wirk is the possibility of automated evaluation of analytical ferrography outputs; the use of them eliminates the crucial disadvantage of ferrographical analysis which is its dependence on the subjective evaluation done by the expert who performs the analysis.

Classifiers are defined as a result of using the methods of machine learning. Based on an extensive database of particles that was created in the first part of the work, the classifiers were trained – as a result, they make the evaluation of ferrographically separated abrasion particles from oils taken from lubricated systems possible. In the next stage, experiments were carried out and optimum classifier settings were determined based on the results of the experiments.

Categories and Subject Descriptors
H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

Keywords
Image analysis, analytical ferrography, classification, wear particles, AdaBoost, image features, machine learning

1. Introduction
Analysis of wear particles and their classification according to respective wear types is a tool that allows to monitor the current state as well as long-term trend of machine part wear (if used repeatedly). In case of an early detection of forthcoming faults, it allows to take preventive measures that can help avoiding the failure of the device.

This work extends the possibilities of the analytical ferrography method which is one of the frequently used methods of particle analysis of operational liquids, especially of lubricating oils. The extension consists of a proposal and implementation of an automatic classifier of wear particles.

Currently, the analytical ferrography method is used mostly because of results of very good quality. This method is based on separation of heterogeneous particles included in oil filling. It facilitates particle sedimentation on a special bottom (mostly a glass board) during the flow of the oil sample through a strong inhomogeneous magnetic field. Particles (wear debris) are then analyzed using a microscope. This method results in determining the wear classes for individual particles and stating the prevalent wear type.

However, the interpretation of results depends on skills of the operator performing the evaluation to a great extent. The aim of this work is to replace the human factor (due to time demands as well as possible subjective viewpoint of the operator) with an automated particle classifier.

The idea of using the analytical ferrography method with tools for automated particle classification is not completely new. Some proposals as well as implementation of systems based on ferrograms can be found in literature [1, 2, 3]. Most of the proposed systems were not finalized up to the practical implementation. A system working in prac-

*Recommended by thesis supervisor: Assoc. Prof. Pavel Zemčík. Defended at Faculty of Information Technology, Brno University of Technology in Brno on August 5, 2011.

Machalík, S.: Image Analysis in Tribodiagnostics. Information Sciences and Technologies Bulletin of the ACM Slovakia, Vol. 3, No. 4 (2011) 23-27

tice is described in [4]; however, it is not suitable for use with analytical ferrography. The described system works with surface textures so the particle images have to be obtained using an electron microscope in a difficult way. Analytical ferrography cannot be used to obtain particle images that would allow analyzing their surface.

The main aim of this work is to introduce a new automated method for particle classification using supervised machine learning. The approach is based on visual similarity of particles within a class.

2. Image Features

The Local Binary Patterns (LBP) method was originally developed for classification of textures but it found its use in image segmentation, face detection and motion detection as well. It is one of methods that work directly with pixels of an image. For each pixel of the input image, its LBP value is calculated from values of pixels surrounding it; the eight pixels closest to it are used most often. The LBP features are usually evaluated over the image converted into grayscale. In this work, center-symmetric modification of the Local Binary Patterns method using low-level image features was used. This feature samples the local neighborhood and compares the sample with a value of the opposite sample. A binary value is generated for each pair of samples. The samples are taken by convolution with rectangular core. Contrary to standard LBP features, the output of CS LBP is not 8-bit code but only 4-bit code. During the course of experiments, other types of image features were also considered (Haar-like features, (E)HOG, LRD etc.). The best results were achieved with CS LBP features although the differences were not really significant. Hence, CS LBP features are used for classification in the final version.

3. Boosting Methods

The aim of the methods of joining the classifiers (boosting) [6] is to improve the classification precision of any classifier. The basic idea comes from an iterative approach. In each iteration, classifiers with the best results and good capability of being mutual complements are chosen among all weak classifiers. This results in a strong classifier that is constructed as a weighed combination of selected simple (weak) classifiers. During each step of learning, one weak classifier is added to this combination. Weak classifiers may even have a relatively low rate of success (just a little better than the estimate) but their combination may result in a strong classifiers with a boosted total classification precision. The evaluation of the resulting classifier is performed as sequential evaluation of responses of all weak classifiers and their weighted sum. The basis for joining several classifiers is to select the first classifier with the classification precision is higher than 50%. Furthermore, other classifiers with precision higher than 50% on their own set of samples are added. Finally, a set of classifiers is chosen so that their classification precision in combination is better than the original classifiers, or, at least, not worse than the best of them – the classification is boosted. The resulting precision of a classifier is usually the same but rather higher than the precision of the worst of the partial classifiers.

AdaBoost (Adaptive Boosting) is currently the most commonly used variant of the boosting method [6]. Similarly to other boosting methods, the aim of using AdaBoost is to increase the classification precision of machine learning algorithms. In this case, the basis is to select weak classifiers and combining them again. During classification, the decisions of several weak classifiers (which can be very simple) are combined, achieving possibly better results than those that could be achieved using individual classifiers. One of advantages is the fact that the resulting strong classifier is very strong and, at the same time, fast enough in real conditions. The AdaBoost algorithm is capable of lowering the error of the resulting classifier on the training set of samples exponentially to any arbitrary level [7]. It is able to produce classifiers with very good properties even if simple classifiers are only used. The selection in each step of learning is performed in a greedy way so that the upper estimate of classifier error is minimized. AdaBoost is also used in combination with neural networks but alternative approaches, e.g. the supporting vector method (SVM), can be used as well.

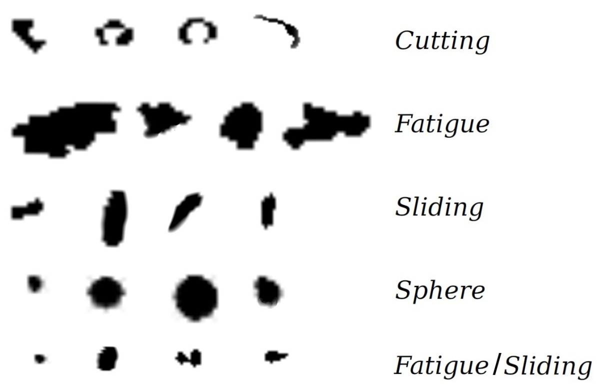

Figure 1: Classes of particles with typical representatives

4. Classification Classes

Five classes which correspond to wear mechanisms typewise were chosen for classifying the wear particles. The following classification classes were used in this work:

- Cutting – cutting wear particles generated as a result of one surface penetrating another.
- Fatigue – this class contains particles that are formed as an effect of repeated passes through the system which results in plastic deformation of particles.
- Sliding – sliding particles have oblong shape and irregular edge. They are smaller than fatigue particles but still larger than 15 microns.
- Sphere – spherical particles can be generated if there is insufficient lubrication or there is a depletion of extreme pressure additives in high load or high stress conditions. Spheres are also produced by fatigue of rolling element bearings.

Later experiments have shown that the success rate of the particle classification is very high (91–96%) with the exception of mutual distinction of classes fatigue and sliding. Based on these results, classification was expanded to contain the fatigue/sliding class which contains these non-classifiable particles.

5. Data Collection and Normalization

In order to obtain enough input data (particle images) for training the classifier, particles from the LNF device were used. The output of this device provides binary images of wear particles obtained from oil. These particles were classified in classes described above by an expert.

The procedure of normalizing the input data consists of nonlinear image scaling, image rotation and transformation by placing the center of gravity into the center of the image.

All particle images must be of constant size (32×32 pixels) prior to machine learning. As the particle size is important for classification, it has to be represented when normalizing. Therefore, the result of normalizing is a set of images of uniform size, preserving the relative particle size.

The class of the particle is independent on the rotation but the rotation strongly increases visual variability of samples within a class. A particle is rotated so its major axis is aligned with the y axis of coordinate system. The major axis is found using the PCA method.

Together with the previous step, the particles are centered in the image so that their center of gravity lies exactly in the center of the image.

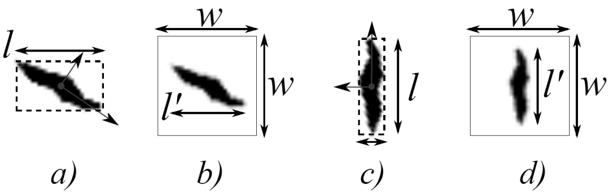

Figure 2: Image normalization. a) source image with particle bounding box and major and minor axes, b) image normalized to size w without rotation, c) rotation of the original image with new bounding box and d) image normalized with rotation.

Different values of normalization parameters were tested. The setting of the parameters in experiments was following:

- The coverage factor c was set constantly to 0.8 in order to fit all particles to the sample and keep some border.
- Sizes of sample images w were 16, 24, 32 and 48 pixels.
- Normalization factor α was 0.02, 0.05, 0.1, 0.2 and 0.5 in order to test the influence of absolute size of particle on the classification accuracy.
- Data were processed both with and without rotation normalization in order to test whether the rotation had influence on the accuracy.

The result of normalization can by expressed as

$$l' = cw(1 - e^{-\alpha l}) \quad (1)$$

where l is length of the longer side of the particle in the original image and l' is length of the longer side of the particle after normalization.

The normalization parameters indicated above influence the classification results in a fundamental way. The classification precision increases considerably when using optimum values. The proposal and a practical test of the normalization methodology is one of the benefits of this paper. Finding the optimum values was the aim of experimental research.

6. Experiments and Results

In order to perform the experiments, four binary classifiers were created. The scheme of their use is shown in Fig. 3. For each setting of normalization parameters, a dataset was created on which each classifier was trained and tested. Classifier designated as CU evaluated particles of the Cutting class, while the SP classifier evaluates the particles of the Sphere class. Due to complicated evaluation of „non-recognizable“ particles on the edge of classes Sliding and Fatigue, the FASL classifier was created which separates Cutting or Sphere particles on one side and Fatigue, Sliding and „non-recognizable“ Fatigue/Sliding particles on the other side. These particles are then assigned the FA classifier that recognizes particles of the Fatigue class. Similarly, SL classifier would be assigned to particles of the Sliding class. There is no need to implement the SL classifier, the Sliding class is a complement of the Fatigue class. Individual classifiers were trained using

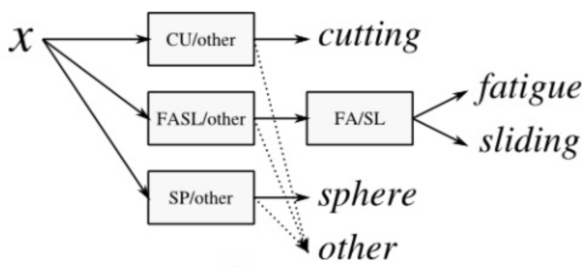

Figure 3: Process of analyzing a particle (X) using four binary classifiers.

all available particles obtained from the LNF. Firstly, all particles were assigned to the correct class by an expert. The classifier trained this way was then tested using particles obtained from ferrograms. Numbers of training as well as testing particles are shown in Table 1. All particles underwent normalization adhering to the same rules as defined in previous experiments. Based on previous results, experiments with CS LBP and LBP features were performed. Uniform rotation of particles around the major axis was performed during normalization in all cases.

Table 1: Numbers of training and testing particles in each classification class.

Classification class	Training	Testing
Cutting	1337	79
Fatigue	2670	279
Sliding	2003	101
Sphere	885	20
Fatigue/Sliding	1607	300

The image size during testing was 24×24 and 32×32 pixels. Tested values of the normalization factor were 0.05, 0.1 and 0.2; all these were used for classifiers CU, SP, FASL and FA.

Following figures show the ROC curves capturing the influence of used setting on the precision of classifiers. The curve progress is not very smooth due to a smaller volume of test data (particles).

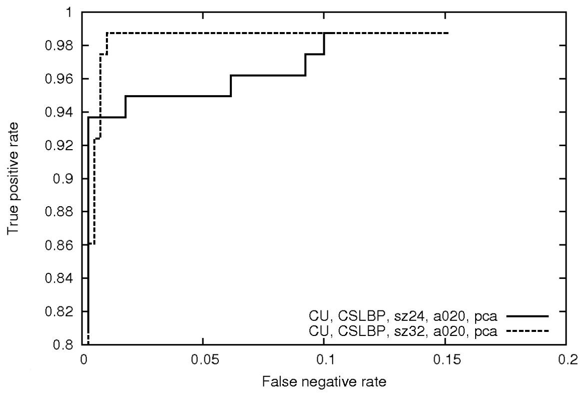

Figure 4: The influence of image size on the classification precision.

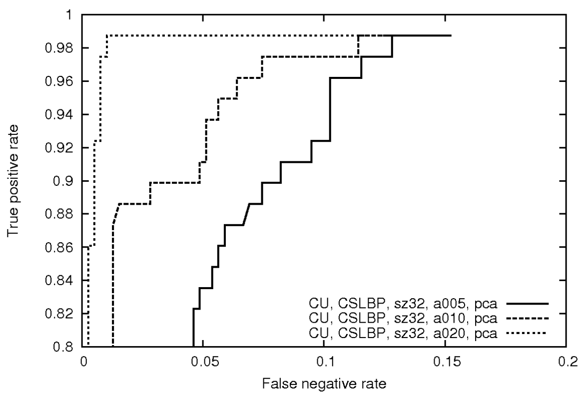

Figure 5: The influence of the normalization factor on the classification precision.

Selected results of particle classification from ferrograms are shown in Table 2. Depending on specific needs, the parameters of normalization can be adjusted and the classification precision of selected classes can be influenced this way.

Table 2: Error rate of particle classification achieved for different values of the normalization factor (LBP/CS LBP features), particle (image) size is 32 pixels, coverage factor is 0.8.

% of error	α=0.05	α=0.1	α=0.2
Cutting	4.19/6.40	4.07/5.35	3.02/1.74
Fatigue/Sliding	3.68/7.33	6.05/6.28	8.61/5.12
Sphere	1.97/3.14	1.62/1.62	0.58/1.28
Fatigue	2.10/4.73	1.57/2.10	7.10/4.21

In the average, the following settings seem to be optimum when using the CS LBP features, image size 32 pixels, normalization factor α = 0,2. The error rate which is under

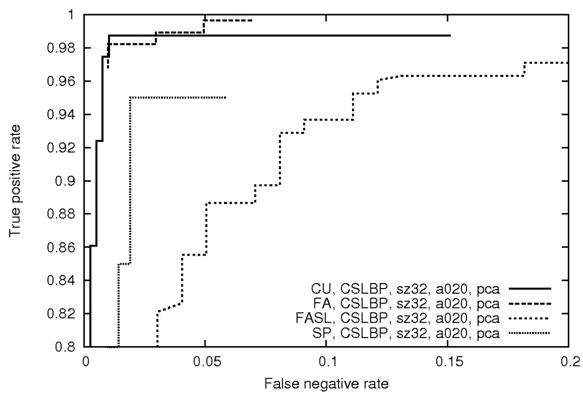

Figure 6: Classification precision using the best settings in average.

the 10% threshold for most settings is very good for the purposes of tribotechnical diagnostics and the automation of the whole process of evaluating the wear is therefore a benefit for practice. Moreover, the assumption is that with growing number of training particles, the error rate of the classifier will go down.

Supplementary materials along with the data and software used for image normalization can be found online [5].

7. Conclusion

The current trend is an effort to automate the process of wear evaluation. One of new approaches is an automated classification of wear particles using the methods of machine learning which was the subject of this work.

The aim of this paper was to examine the possibilities of automated classification of wear particles. The classifier that was created allows to perform an automated analysis of the state of monitored machines from the wear point of view and it becomes much more accessible as a result. Due to the use of the automated classifier, the evaluation becomes less biased, simpler and, last but not least, cheaper solution.

The output of the paper is the procedure of proposing and implementing an automated classifier of wear particles which uses machine learning methods for analyzing the particle images. These images get normalized and they are used as an input for training the classifier afterwards. During the training, specific image features are evaluated in the particle images (the best results were achieved using the CS LBP features) which are then searched for in tested images during classification.

The classification precision depends on the number and correct classification of training particles to a considerable extent. Particle images achieved by using laser analyzer of particles were used for training the classifier. Firstly, these particles were assigned to selected wear classes by an expert; then, they were used as an input for training. Currently, the database contains about 9 000 particle images and more will be added continuously.

During the course of experiments, various methods of machine learning were tried; the best results of them were achieved by using the AdaBoost algorithm. It was proven by experiments that the results of using the AdaBoost method for image classification are comparable (or even better in many cases) to the results of the alternative SVM method or of neural network.

For the purposes of machine learning methods, a mathematical description of the image in the form of image features. The CS LBP and LBP were evaluated as suitable.

It was proven by experiments that the influence of normalization of particle images on the classification precision is crucial. Determination of optimum values of normalization parameters allowed to achieve higher classification precision, being hence a fundamental step in the stage of preparing the input data for classification. The proposal as well as practical testing of the methodology of normalization are the main benefit of this work.

Achieved results show that the use of an automated classification of particles in operation can produce results which can be used in practice but which cannot be achieved by using other methods in many cases. Currently, the error rate of classification is below the 10% threshold depending on the settings of the classifier and the tested class. The classification precision of processing other operational samples will be higher in real applications due to statistical processing of data.

The achieved precision indicates an improvement as compared to hitherto results where ferrograms are evaluated by a trained operator but the result is subject to subjective evaluation. Even if knowing the rules of particle classification, the rate of success of a non-trained laboratory operator performing the evaluation just by comparison with a set of particles is 60–70 %. If the database of samples normalized in a suitable way is large enough, the classification based on machine learning methods seems to be favorable and the results achieved represent a promise for further development and making the classifier results more exact. The aims determined at the beginning of the solving process were thus achieved successfully.

The tool created for the particle classification will be used in practice mostly for monitoring the progress of wear on samples taken in a longer time interval successively in order to perform the trend analysis. Evaluation of the current state based on one measuring is a problem, the number and shapes of particles may differ for different machines. At the beginning, the classifier will be used in the laboratories of the Jan Perner Transport Faculty of the University of Pardubice.

Acknowledgements. This research was supported by the research project MSM 0021627505 ”Transport systems theory.

References

[1] G. P. Stachowiak, G. W. Stachowiak, P. Podsiadlo. Automated classification of wear particles based on their surface texture and shape features. *Tribology International*, volume 41, issue 1, 2008, s. 34–43, ISSN 0301–679X.

[2] A. M. Nazar, F. A. Silva, J. J. Ammann. Image Processing for Particle Characterization. *Elsevier Science*, volume 36, issues 4–5, State University of Campinas, Brazil, 1996.

[3] K. Xu, A. R. Luxmoore. An integrated system for automatic wear particle analysis. *Wear*, volume 208, issues 1–2, 1997, s. 184–193, ISSN 0043–1648.

[4] G. W. Stachowiak. Numerical characterization of wear particles morphology and angularity of particles and surfaces. *Tribology International*, volume 31, issues 1–3, 1998, s. 139–157, ISSN 0301–679X.

[5] R. Juránek, S. Machalík, P. Zemčík. Wear debris analysis of type , August 2011. URL http://medusa.fit.vutbr.cz/particles/.

[6] R. O. Duda, P. E. Hart, D. G. Stork. *Pattern Classification*. Wiley-Interscience, 2011, ISBN 0–471–05669–3.

[7] Y. Freund, A. Schapire. A Decision-theoretic Generalization of Online Learning and an Application to Boosting. In *EuroCOLT '95 Proceedings of the Second European Conference on Computational Learning Theory*. Springer-Verlag London, 1995, ISBN 3–540–59119–2.

Selected Papers by the Author

S. Machalík, R. Juránek, P. Zemčík. Machine Learning-Based Classification of Wear Debris. *Radioengineering*, Brno University of Technology, 2011, ISSN 1210–2512.

R. Juránek, S. Machalík, P. Zemčík. Analysis of Wear Debris Through Classification. In *Advanced Concepts of Inteligent Vision Systems 2011*, LNCS, Springer, p. 11.

S. Machalík, R. Juránek, P. Zemčík. Automatická klasifikace částic opotřebení. *Tribotechnické informace*, Business Media CZ, s.r.o., 2011, issue 1, s. 18–19, ISSN 0040–1064.

S. Machalík, R. Juránek, P. Zemčík. Wear Debris Analysis in Transport. In *Proceedings of the 5th International Scientific Conference Theoretical and Practical Issues in Transport*, Univerzita Pardubice, 2010, s. 25–31, ISBN 978–80–7395–244–0.

S. Machalík. Metody analýzy opotřebení motorů. In *Sborník mezinárodnej vedeckej konferencie IKTAM 2010*, Žilinská Univerzita v Žilině, 2010.

S. Machalík, F. Machalík. Obrazová analýza částic opotřebení. In *Sborník mezinárodní konference Dopravní systémy 2009*, Institut Jana Pernera, o.p.s., 2099, s. 25–40, ISBN 978–80–86530–63–5.

S. Machalík. Modern Techniques of Wear Debris Analysis. In *Sovremennyj naučnyj vestnik*, Kyjev, 2008. Vyd. Rusnaučkniga, s. 82–85, ISSN 1561–6886.

S. Machalík. Modern Techniques of Wear Debris Analysis. In *Sovremennyj naučnyj vestnik*, Kyjev, 2008. Vyd. Rusnaučkniga, s. 82–85, ISSN 1561–6886.

E. Schmidová, J. Machalíková, S. Machalík. Kvantitativní metody v metalografickém hodnocení jakosti svarových spojů. In *Sborník 6. odborného semináře Svařování v železniční dopravě*, 2005, Česká Třebová, Univerzita Pardubice, s. 107–118, ISBN 80–7194–740–7.

J. Machalíková, S. Machalík, E. Schmidová. Využití obrazové analýzy při hodnocení maziv a konstrukčních materiálů pro dopravní prostředky. In *Sborník mezinárodní konference informačních technologií v dopravě – INFOTRANS 2005*, 2005, Univerzita Pardubice, s. 182–192, ISBN 80–7194–792–X.