07 - 10 September 2009

PROCEEDINGS

54. IWK

Internationales Wissenschaftliches Kolloquium

International Scientific Colloquium

Information Technology and Electrical Engineering - Devices and Systems, Materials and Technologies for the Future

Faculty of Electrical Engineering and Information Technology

Startseite / Index:
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TECHNISCHE UNIVERSITÄT
ILMENAU

Impressum

Herausgeber:	Der Rektor der Technischen Universität Ilmenau Univ.-Prof. Dr. rer. nat. habil. Dr. h. c. Prof. h. c. Peter Scharff
Redaktion:	Referat Marketing Andrea Schneider Fakultät für Elektrotechnik und Informationstechnik Univ.-Prof. Dr.-Ing. Frank Berger
Redaktionsschluss:	17. August 2009

Technische Realisierung (USB-Flash-Ausgabe):
Institut für Medientechnik an der TU Ilmenau
Dipl.-Ing. Christian Weigel
Dipl.-Ing. Helge Drumm

Technische Realisierung (Online-Ausgabe):
Universitätsbibliothek Ilmenau
ilmedia
Postfach 10 05 65
98684 Ilmenau

Verlag:
isle
Verlag ISLE, Betriebsstätte des ISLE e.V.
Werner-von-Siemens-Str. 16
98693 Ilmenau

ISBN (USB-Flash-Ausgabe): 978-3-938843-45-1
ISBN (Druckausgabe der Kurzfassungen): 978-3-938843-44-4

Startseite / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=14089

VISUAL QUALITY INSPECTION OF TEXTURED MATERIAL SURFACES WITH ASSISTANCE OF SELF-ORGANIZING MAPS

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ABSTRACT

This paper represents recent results concerning development of a software framework for time and effort-saving implementation of diagnostic programs for visual inspection of textured material surfaces. The explanations conclude with the presentation of first practical applications.

Index Terms— image processing, Kohonen map, neural network, SOM, surface inspection, texture analysis

1. INTRODUCTION

This project aimed at the development of a basic conceptual programming structure (framework), allowing a rapid implementation of diagnostic routines for visual inspection of flat, textured material surfaces. Framework includes a combination of image processing algorithms and soft computing techniques. For the latter, integration of Neural Networks (NN) were preferred. NN model types Multilayer Perceptron (MLP) and Self-Organizing Map (SOM) were taken into consideration.

For the implementation of the framework some conditions were set:

- Preferably, diagnostic programs must be executable under the MS Windows® operating systems. Considering the increased security and reliability of alternative OS, a porting to Linux should come along with a minimum of time investment. Therefore, platform specific features must be avoided.
- Online inspection requires the interpretation of textural attributes, which should be calculated with low computational costs.

To satisfy this conditions, software framework was implemented in C++, which allows high execution speed and good portability. Additionally, a sub-goal is a minimum amount of preliminary work, which must be invested to prepare NN for inspection tasks.

The preliminary process provided by the framework is structured in:

- Database generation: Database consists of textural features, extracted from digital images. Optionally, images can be preprocessed for quality reasons.
- Network training phase: Test data presentation, associated with an iterative self-modification of the NN.
- Network recall phase: NN will be confronted with unknown datasets.
- Network rating: If a reasonable quality of trained NN cannot be achieved, training and recall will be repeated after adapting NN configuration parameters.

After successful rating NN can be considered as ready for practical operation.

2. DATA PROCESSING

2.1. Image preprocessing

Matrix cameras were considered as sensor devices. To cope with rough conditions an optical inspection system is confronted with, several basic algorithms for image enhancement were implemented: Gray value variations, caused by inhomogeneous illumination, can e.g. be compensated by histogram equalization.

After capturing textured material surfaces with varying quality levels, resulting images were partitioned into tiles (sub-images). Their size depends on occurence of possible defects. Sub-image size specifies as well the area a texture defect can be localized within.

2.2. Image feature extraction

With respect to formerly mentioned restrictions concerning calculation costs, a range of textural attributes is calculated for every sub-image. Texture analysis is limited to statistical approaches. Some basic attributes, like the scope of gray values, can be derived from histogram. A range of widely used textural attributes can be compiled from

- Gray-level Cooccurence Matrix (GLCM), which is derived from pairwise pixel intensity statistics (see Haralick et al. [1]),
- Gray-tone Difference Matrix (GTDM), which is computed by measuring the difference between gray value of a pixel and averaged gray value over a squared window centered at it (see Amadasun & King [2]).

Furthermore, the Local Binary Pattern (LBP), introduced to the public by Ojala et al. [3], is calculated for every sub-image as a gray-scale invariant texture attribute.

All calculated feature values are collected in a database. The relevance of a feature to the good/bad rating of material surface varies in dependence on the inspection task.

2.3. Inclusion of expert knowledge

Expert knowledge has to be added to the database to fulfill all conditions for training and recall of a NN. Therefore, every sub-image has to be examined by an expert, who assigns the categorical attributes ”good” or ”bad” due to the quality of the pictured surface. The possibility to set such simple attributes supports the human habit of decision-making during inspection by manpower. Nevertheless, influence of subjectiveness can be reduced as far as possible.

A suitable codification is needed for further handling of these categorical attributes. In this case, a representation according to the simple formula

$$x = \begin{cases} 0 & \text{if rated GOOD} \\ 1 & \text{if rated BAD} \end{cases} \tag{1}$$

allows inclusion of expert knowledge in the database.

Usage of a higher amount of attributes is allowed for the case, that attributes correlate with intensity/size of appearing texture defects. Representation should be realized by equidistant values in the range of $\{0 \ldots 1\}$ (see section 6.2 for an example).

3. NEURAL NETWORKS

3.1. SOM in general

Self-Organizing Maps (SOM), which were introduced by Kohonen [4, 5], possess a simple structure in comparison to other NN model types. In the simplest case, all neurons of a SOM are arranged in a so-called competitive layer with rectangular/squared shape. Every single neuron is assigned to a reference vector $W(x, y)$ containing the weights, whose length is equal to the dimensions of training dataset.

Training utilizes competitive and unsupervised learning. When a training dataset X is presented to the SOM, its distance to all reference vectors is computed. The neuron with shortest distance is declared as Best Matching Unit (BMU). BMU weights and weights of neurons in an influence radius r are adjusted to X. Magnitude of adjustment is controlled by following functions:

- learning function $L(t)$, which is monotonically decreasing with time,
- neighborhood function $E(t, r)$, which is monotonically decreasing with radius r and time.

This process is repeated several times until a convergence criteria is fulfilled or an iteration limit is reached. After training content of the training database is partitioned into centroids. Further details are i. a. given in Knieling [6] and Zeil [7].

SOM, also known as Kohonen maps, have been successfully applied for clustering and classification tasks, image segmentation and as a visualization tool for high-dimensional data. The modeling approach used for the purpose of texture quality rating is described in the next section.

3.2. SOM modeling approach

A new interpretation scheme of the reference values allows the full integration of expert knowledge during training phase of the SOM:

During training phase SOM is confronted with the attributes of texture examples along with assessment attributes, paraphrasing the quality level according to expert knowledge. BMU will be chosen by the minimum Euclidean distance between full training dataset X and full reference vector W.

The recall phase includes comparison of expert rating with quality evaluation performed by the trained SOM. Distance measurement is limited to $x_1 \ldots x_{n-1}$ and $w_1 \ldots w_{n-1}$; w_n of the BMU will be interpreted as model output y (see fig. 1). Hence, expert knowledge is always located in the last value of all reference vectors.

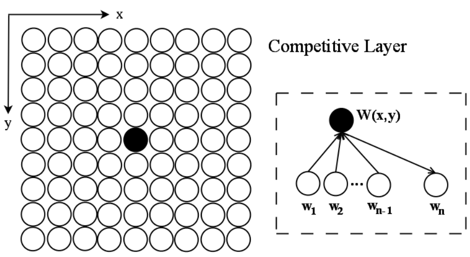

Fig. 1. Scheme of a SOM structure (left) and SOM neuron with its reference vector (right).

3.3. Evaluation criteria

Various types of errors are considered after recall phase for the evaluation of quality:

Mean squared error e_{MSE} as well as minimum absolute and maximum absolute error indicate divergences between expert knowledge and model response.

Quantization error e_{qu}, which is defined as

$$e_{\text{qu}} = \frac{1}{n} \cdot \sum_{i=1}^{n} ||X_i - W_{\text{BMU}}(X_i)||, \quad (2)$$

where n is the number of recall data-vectors and X stands for a single data-vector, characterizes the achieved resolution of the quantization of data. Low values of e_{qu} indicate a successful data representation by SOM.

The topological error is given by the formula

$$e_{\text{topo}} = \frac{1}{n} \cdot \sum_{i=1}^{n} f(X_i) \quad (3)$$

where f is defined as

$$f(X_i) = \begin{cases} 0 & \text{if BMU}_1 \text{ and BMU}_2 \text{ adjacent} \\ 1 & \text{otherwise,} \end{cases} \quad (4)$$

and BMU_1 and BMU_2 stand for first and second best matching unit for X_i. According to the definition of Uriarte [8], horizontal, vertical and diagonal adjacency is considered. Topological error e_{topo} indicates preservations of topological relationships in the data. Quantization and topology preservation often conflict for the case, that dimension of X is higher than dimension of SOM grid (see Kirk & Zurada [9]).

4. PARAMETER ANALYSIS

4.1. Goals

The configuration of a SOM mainly includes parameter settings like number of neurons, initial learning rate and map grid shape as well as the selection of initialization scheme and training method. For easy usability of the software framework, it is necessary to reduce amount of this preliminary work. A comprehensive parameter analysis aims at the formulation of a helpful Best Practice Guideline. Furthermore, interpretation of the results and conclusions allow the implementation of a semi-automated selection of suitable parameters for a given database.

Therefore, 25 texture datasets were derived from the Brodatz texture database, the standard for evaluating texture algorithms, which represents various kinds of natural and synthetic surfaces. Samples are shown in fig. 2.

Formerly mentioned texture features were calculated over all sub-images of the generated texture albums to provide a data basis for training and recall of the SOM. Primary feature selection was done by reducing highly correlated texture attributes. Training was performed using the given datasets with randomly permutated labels.

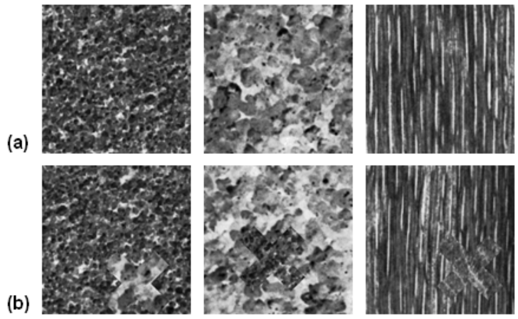

Fig. 2. Samples from texture albums, derived from the Brodatz texture database, containing intact surfaces (a) and structural defects (b).

4.2. Results

Required functionality could be achieved by simple SOM structures like rectangular formations of neurons. Briefness of calculation during this process was achieved by using an initialization scheme introduced by Su et al. [10] and an in-house developed training algorithm. For the latter the adjustment of the neuron weights as described in section 3.1 will not be executed for every iteration. Instead a cache algorithm is used, which reduces the total amount of required arithmetic operations.

Expenditure of time can be reduced by carrying out formulated Best Practice Guidelines, containing e. g. the following conclusions:

- A preferred application of rectangular map grids, which was recommended by Zeil [7], can be confirmed. An increase of height-weight ratio comes along with a SOM with poorer quality, indicated by higher values of e_{MSE}.
- It turned out that in all given cases the minimization of e_{qu} takes precedence over topology preservation.
- Neighborhood function E should be defined as Gaussian function.

Furthermore, parallel modeling approaches turned out, that in some cases the required functionality cannot be achieved with MLP. Based on the results, the SOM were firmly integrated into the framework. In addition to this, semi-automated parameterization was realized.

5. FEATURES OF THE RESULTING FRAMEWORK

The key features of the resulting framework can be specified as follows:

- The framework enables Rapid Application Development for diagnostic routines.
- Teach-in part is comparatively less time-intensive and simplified by using a minimum of attributes for the representation of expert knowledge.
- Included image enhancing algorithms allow increasing robustness of feature extraction.
- Calculation algorithms for the chosen texture features have a high potential for parallelization. In dependence on hardware architecture for execution of diagnostic routines, inspection process can be speeded up by using full CPU capacity.
- The framework itself allows the integration of additional functions depending on special needs of the inspection task. Besides, portability to alternative OS is given.

Nevertheless, the transparent functionality of SOM increases acceptance for integrating Soft Computing methods into inspection processes.

6. FIRST PRACTICAL APPLICATIONS

6.1. Inspection of reflective surfaces

As a first practical application a framework-based diagnostic program for inspection of highly reflecting mirror surfaces was successfully tested under sub-optimal light conditions. Surfaces were captured by

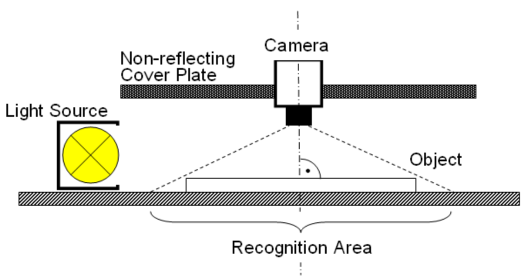

Fig. 3. Test device for inspection of highly reflecting mirror surfaces.

a matrix camera in an experimental device with dark field illumination (see fig. 3). The backside of the non-reflecting cover plate is pictured as a homogeneous background on the mirror surface. Feasibility study aimed at identification and differentiation of irreparable surface defects as well as fouling (see fig. 4). Depending on the inspection results, a subsequent

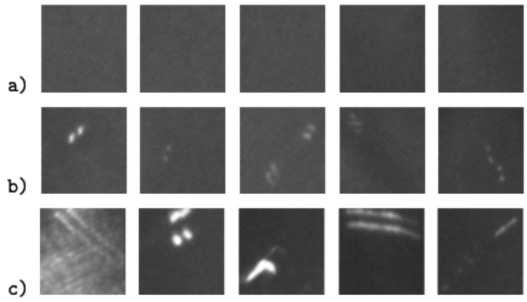

Fig. 4. Sub-images of mirror surface without flaws (a), with fouling (b) and irreparable defects (c).

treatment of objects (cleaning of the surface or complete refusal) should be initiated.

As a result slight inhomogeneities of the textures, caused by illumination, were successfully compensated by performing histogram equalization. Functionality can be provided by a rectangular SOM grid with 4×22 neurons, using maximum gray value (histogram-based feature) and cluster shade (GTDM-based attribute) for evaluation criteria.

6.2. Classification

A classification of brushed metal plates based on micrographs as seen in fig. 5, was realized by replacing assessment attributes with gradings. In this case codifi-

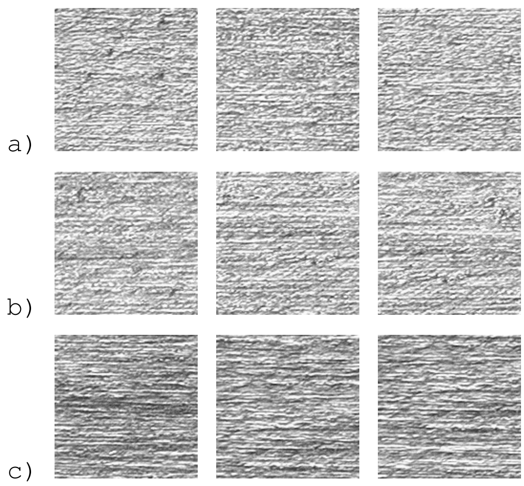

Fig. 5. Microscopic sub-images of (a) soft- (b) medium- and (c) hard-brushed metal surfaces.

cation of expert knowledge complies with the scheme

$$R = \begin{cases} 0.0 & \text{if soft-brushed} \\ 0.5 & \text{if medium-brushed} \\ 1.0 & \text{if hard-brushed.} \end{cases} \quad (5)$$

Classification task was solved by a rectangular SOM with 7×9 neurons. 8 different textural attributes were applied as distinguishing features.

7. ACKNOWLEDGMENTS

Investigations have been financed by the Saxonian Ministry of State for Science and Art (SMWK) under grant no. 4-7531.60-02-5150-07/15.

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