Identification and Classification of Color Textures

Mattias Mende [0000-0002-4458-6539], Thomas Wiener [0000-0002-9912-0162]

Fraunhofer Institute for Machine Tools and Forming Technology IWU,
Chemnitz, Germany
www.iwu.fraunhofer.de
mattias.mende@iwu.fraunhofer.de,
thomas.wiener@iwu.fraunhofer.de

Abstract. This article describes, how color textures can be reliably detected and classified in the production process independent of external parameters such as brightness, object positions (translation), angulars (rotation), object distances (scaling) or curved surfaces (rotation + scaling). The methods described here are also suitable for reliably classifying at least 18 color textures even if they differ only slightly from each other optically. The online classification of color textures is a classic task in the wood, furniture and textile industry. For example, unwanted defects or partial soiling on moving webs can be reliably detected regardless of fluctuations in brightness and/or shadows during process operation. Algorithms has been developed for teach-in with RGB-HSI-transform, set fewer segments on the color textures of each class with e.g. 24x24 Pixel, use suitable transformations {HSI}, e.g. 2D-FFT for formation characteristic 2D spectral mountains in these segments, extraction of statistical features and setting up the individual classifiers. Algorithms has been developed for identification & classification in process operation with extraction of statistical characteristics and methods of robust classification. The implementation of the methods, the triggering of the color cameras, the processing of the color information including the output of the results to the process control is done with the data analysis program Xeidana®.

Keywords: Optical Image Processing, Identification, Classification, Color Textures, Process Control, Color Sphere Model.

1 Introduction

The applications of optical image processing cover almost all areas of daily life as well as in production, manufacturing and research. They can be assigned to five essential fields, see Fig.1.1.

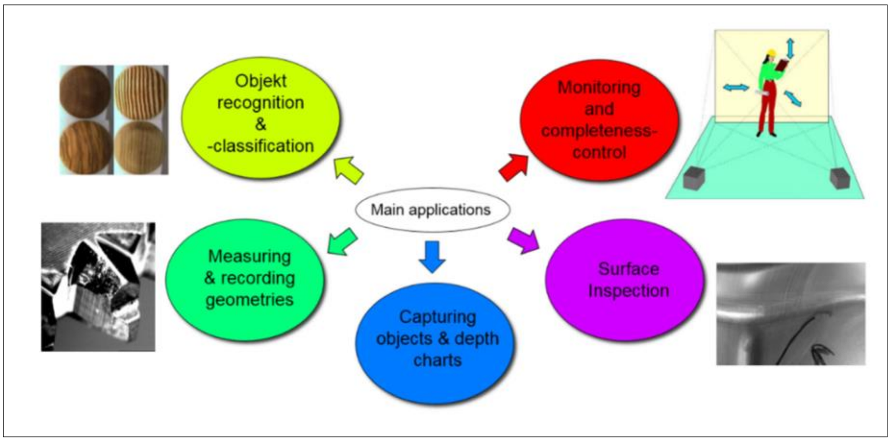

Fig.1.1. Important fields of application of optical systems

Important fields of application are object recognition and classification, monitoring and control of visible areas, inspection of object surfaces, recording the (3D) positions of objects or measuring their 3D geometries. In this paper the automatic recognition and classification of objects using existing textures will be presented. Textures are characteristic regular or disordered patterns, which can be found on the surfaces of objects, see Fig.1.2.

Fig.1.2. Example of a color texture (*Vanessa atalanta*)

2 Task definition

During the actual classification process, all objects of one type are grouped together in a uniform class. New classes are created for objects of a new type. An important task in classification is to separate textures of different classes from each other (selectivity), but at the same time to allow textures with small deviations within the class (immunity to interference) [1].

In particular, the correct result of the classification should not be affected even if typical deviations occur in the production process, e.g.

- The objects change their positions in the camera image, (T-) translation invariance
- The color textures of individual objects are rotated, (R-) rotation invariance
- The sizes of the textures change, (S-) scaling invariance
- The ambient brightness changes and thereby the integral brightness of the image changes
- Partial shadows appear on the textures
- There is partial soiling on the colour textures
- The textures lie on spherically curved surfaces and are therefore distorted in the camera image (RST invariance)

3 Methods and procedures

Mostly color cameras are used for optical image processing. The method of classification described here is therefore based on color textures, but is also well suited for b/w textures. The actual process of classification is divided into 2 steps; the prior learning of suitable features of the textures (1.) as well as their recognition and online classification (2.) in the process, see Fig.3.1.

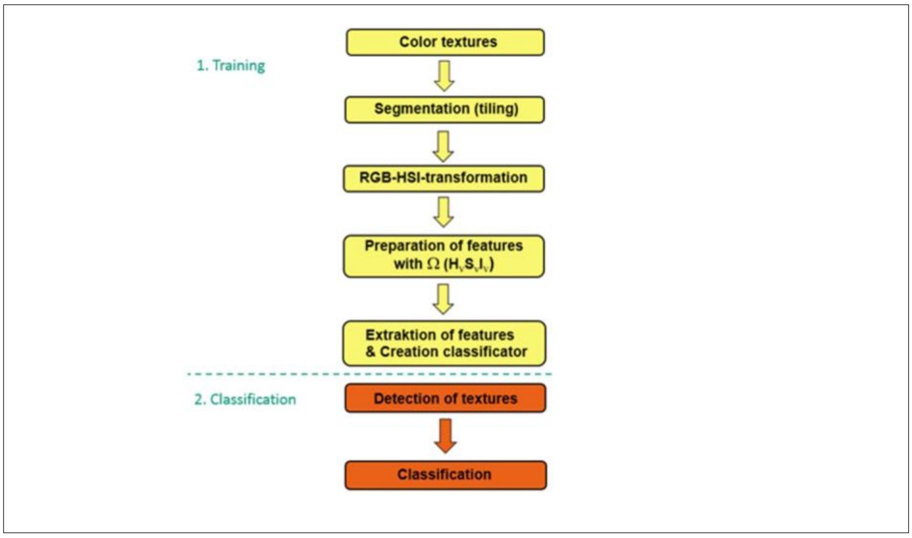

Fig.3.1. Scheme of the 2 phases and individual sub-steps for online classification of color textures

Both for teaching the textures and for their classification in process operation, the textures are divided into individual segments (segmentation). This corresponds to the model of nature with a successive rejuvenation of the number of image channels from the retina to the following bipolar cells according to the visual process.

3.1 Segmentation (tiling)

During the teach-in process one or more representative segments (tiles) with e.g. 16x16 or 32x32 pixels edge length are taken from the textures of each relevant object class, see Fig.3.2.

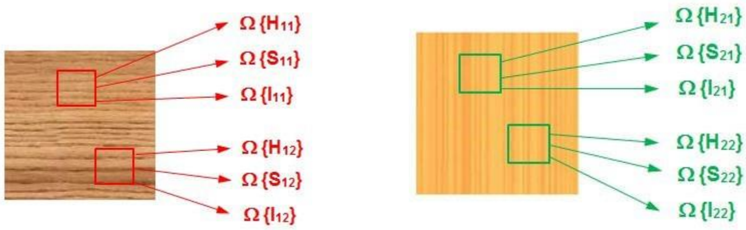

Fig.3.2. Teaching of characteristics with square segments for the classification of 2 textures

3.2 RGB-HSI transformation

A previous HSI transformation of each RGB color pixel proves to be advantageous. It forms the basis for obtaining invariant features and ensures by simple means an additional invariance against changes in brightness, partial shading etc., Fig.3.3.-6.
The HSI model used for this purpose is based on the HSI color sphere model according to [2]. Compared to other colour models, this model has a spatially vivid representation of hue (**H**), colour saturation (**S**) and brightness (**I**) and at the same time a largely consistent and unambiguous mapping of the entire set of all points of the RGB colour space to the points of the HSI colour space.

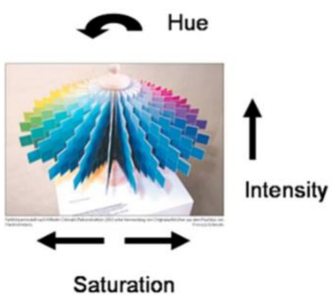

Fig.3.3. RGB HSI transformation with color sphere model according to [2]

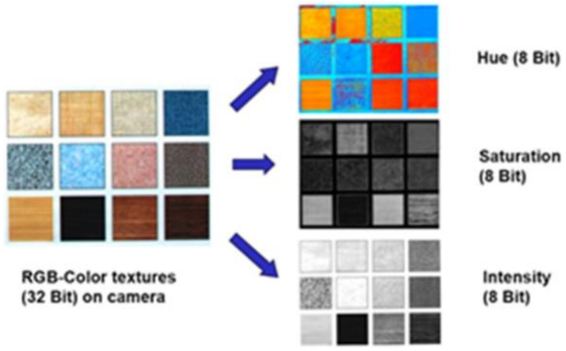

Fig.3.4. 32Bit RGB HSI transformation into 8Bit hue (**H**), colour saturation (**S**) and brightness (**I**) images

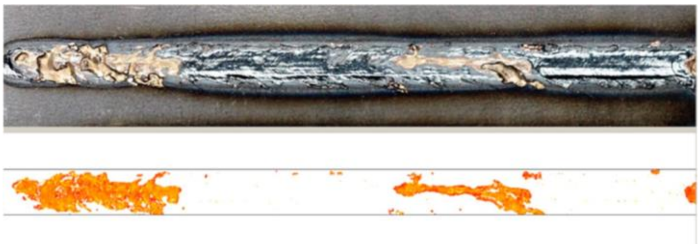

Fig.3.5. RGB HSI transformation for hue (H) during laser desoldering of silicon bronze (above original, below result of analysis) [3]

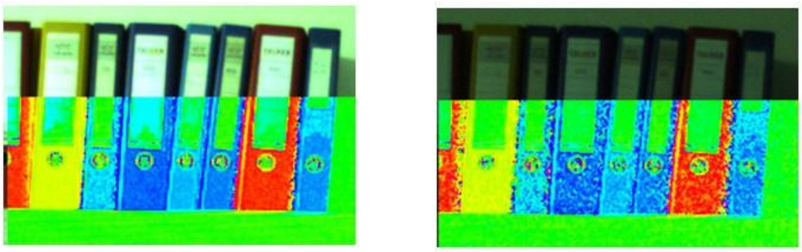

Fig.3.6. Invariance of the hue image (lower half) compared to brightness variations on real 32-bit RGB color textures (upper half) (exposure time in the left image: 8ms, right image 1ms) [4].

3.3 Preparation of characteristics

Characteristic features are extracted from the tiles of each class for the classification. The HSI values of the individual segments are first processed, i.e. subjected to a suitable transformation {HSI}. From this, m-characteristics are then generated within each class. Depending on the number 'n' of segments used, these characteristics are summarized in m-dimensional clouds with n-points each. From the point clouds those characteristics can be extracted for each class, which have the best invariance properties against external parameters such as changes in brightness, scaling, rotation or distortion [4], see Table 3.1.

Table 3.1. Invariance properties of statistical characteristics used in 2D FFT

Characteris-tics	Event in original area						
	Change in bright-ness	Trans -lation	Scal-ing	Scal-ing*	Rota-tion	Rota-tion*	Dis-tortion
Focus u	o	o	-	o	-	-	-
Focus v	o	o	-	-	-	o	-
Variance u	o	o	-	o	-	o	o
Variance v	o	o	-	-	-	o	
Mean value	-	o	o	o	o	o	o
Variance	-	o	o	o	o	o	o
Inverse dif-ference torque	o	o					
Energy	o	o	o	o	o	o	o
Entropy	-	o	o	o	o	o	o
Correlation	-	o	o	o	-	-	-
Contrast	o	o	-	-	-	-	-
Homogeneity	o	o	-	-	-	-	-

O invariant, - non-invariant,
* after transformation from cartesian coordinates to polar coordinates

The transformations {HSI} listed below offer, among other things, the possibility of bringing about an extraction of suitable and partially invariant characteristics after ap- propriate preparation of the segments:

- Histogram analysis
- Fast Fourier Transformation (FFT)
- Hough Transformation
- Gabor transformation
- Local Binary Pattern (LBP) approach

With methods such as the Local Binary Pattern (LBP) approach [5], characteristics with invariant properties can be extracted without prior transformation {HSI}.

In order to achieve additional better properties regarding immunity to interference (shadows, contamination) and at the same time high separation efficiency for similar textures belonging to other classes, methods with robust classification are used. Modern methods of classification use numerical compensation methods, e.g. the method of least squares, as well as methods of fuzzy classification based on probabilistic models, see Fig.3.7. For their description, for example, the minimum sympathy difference (shown in green), which is a measure of the minimum distance between two texture classes in the n-dimensional feature space, is suitable. The sympathy difference then describes the affiliation to a texture class.

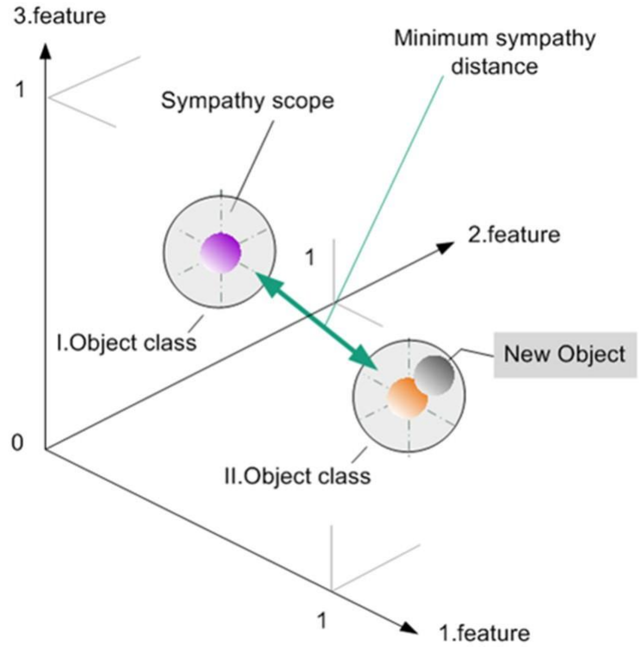

Fig.3.7. Display of the point cloud of a new texture (New Object) for robust classification into one of n = 2 texture classes with m = 3 used characteristics

In [6] the number of texture classes corresponds to the number of m-dimensional point clouds. Their positions, shapes and characteristics are important parameters for each class. As a result of the classification, the class with the highest sympathy is used, i.e. where the sum of the distance values of the feature vectors is minimal. However, if this sympathy is smaller than the minimum sympathy SMS or the difference to the next smaller sympathy is smaller than the minimum sympathy difference SMD, the point cloud is rejected as unclassifiable. In the following Table 3.2., different methods are listed, which are in principle suitable for the robust classification of color textures.

The methods listed in Table 3.2. were implemented in the existing universal data analysis program Xeidana® [10].

Table 3.2. Overview of Robust Classification Methods

Procedures	**Advantages**	**Disadvantages**
Support Vector Machine [7, 8]	+ Very good with a large number of features + Complex classes can be taught	- Possibly complex search for parameters for kernel function
Multilayer Perceptron [9]	+ Complex classes can be taught	- Search for optimal network topology and parameters
Multiple linear discriminant analysis [9]	+ Parameter-free method	- Linear classifier
Radial basic function net-work [9]	+ Complex classes can be taught process → better convergence than with multilayer Perceptron	- Very extensive parameter set

3.4 Feature Extraction & Create Classifier

The program Xeidana® (eXtensible Environment for Industrial Data ANAlysis) is used for the feature extraction and the creation of the classifier. The program Xeidana® is written in C#.

It comprises of an extensible development environment for solving data analysis tasks in the industrial sector, Fig. 3.8.

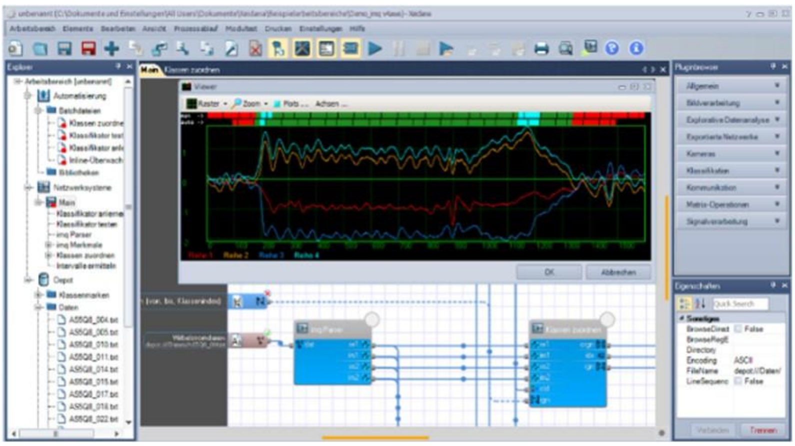

Fig.3.8. Xeidana® user interface with modular functionality

Xeidana® is also used for the classification and visualization of large amounts of data. With the help of the extensive repertoire of algorithms and procedures, colour textures, for example, can be classified. The software has a modular structure and can be extended with new functionalities using a variety of different libraries.

Fig.3.9. shows the user interface with which colour textures are both taught and classified. The left window shows 18 different colour textures which are to be taught. The right part of the user interface contains the functionality for selecting the RGB and HSI color channels, setting segments of variable size, e.g. with 16x16 or 32x32 pixels, and classifying the textures.

The segments are set with the mouse on the texture, see red tile on the upper texture. The extraction of the characteristics can be done with Histogram Analysis, Fast Fourier Transformation (FFT) or Gabor Transformation

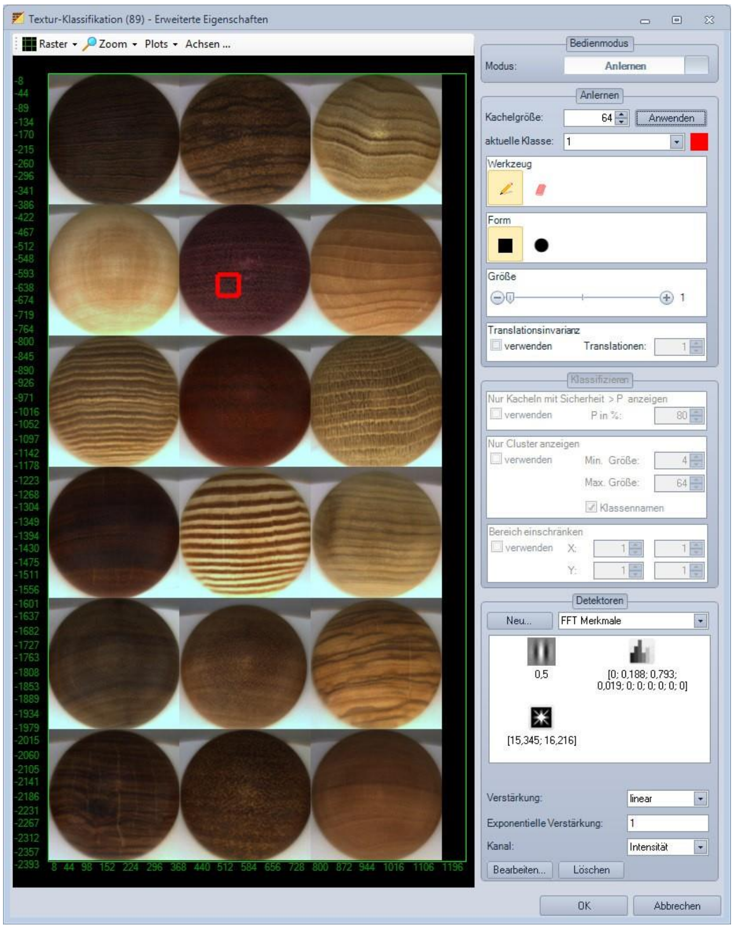

Fig.3.9. Xeidana® user interface for teaching and classifying color textures

In Fig.3.10. n-dimensional feature vectors of the individual classes are shown. By pair- wise combination of two characteristics in each case, in the plan view (left picture) suitable characteristics are compared and selected by assessing their separation perfor- mance (Features of the LBP procedure).

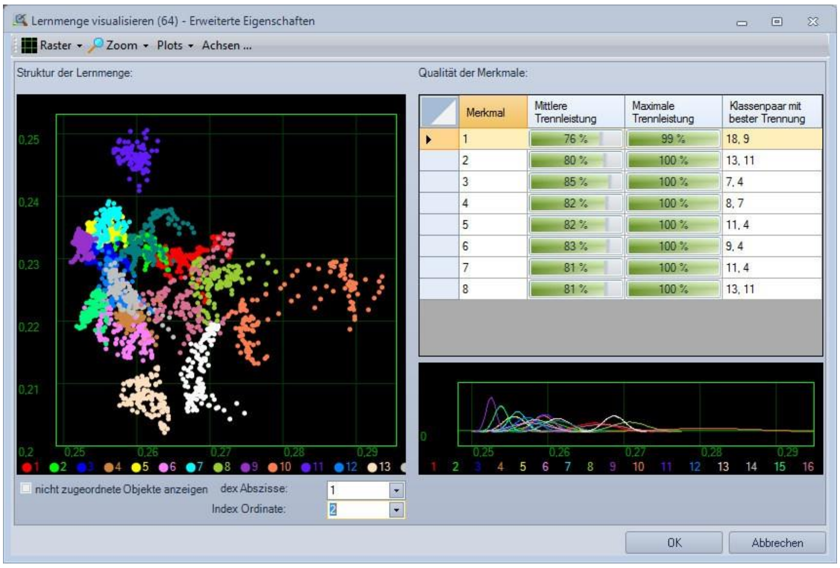

Fig.3.10. Xeidana® user interface for displaying the n-dimensional feature vectors of the individual color texture classes

Fig.3.11. shows the module for Robust Classification used for setting the parameters of the classifier and for automatic parameter optimization using the Support Vector Machine as an example.

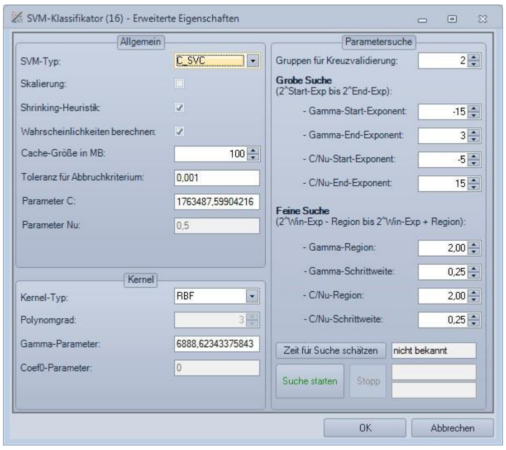

Fig.3.11. Xeidana® user interface for Robust Classification

4 Results & industrial application examples

In order to create environmental conditions for the classification of color textures similar to those in process operation, a special test stand with a conveyor belt (width 1m, length 4m) was set up at Fraunhofer IWU. The asynchronous triggering of the individual cameras, the processing of the image information and the transfer of the classification results are based on the data analysis program Xeidana®, see Fig.4.1.

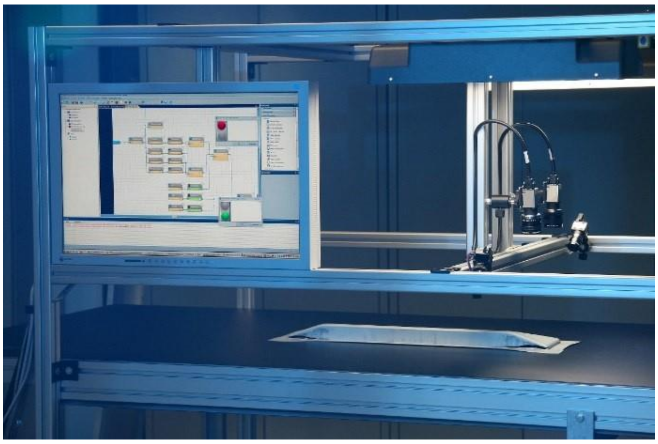

Fig.4.1. Test rig for online classification of color textures on moving objects

To demonstrate the performance of the Xeidana® program, a demonstrator was cre- ated, see Fig. 4.2. which consists of a camera and a turntable with 10 different types of wood. The grains and colors of the 10 types of wood are different, but in some cases they differ only slightly from each other. The aim was to achieve a correct clas- sification over their entire surface despite the spherically curved surfaces and the re- sulting variations in colour textures in distance and angular position. The result of the classification is shown in Fig.4.3.

Fig.4.2. Demonstrator with 10 wood species

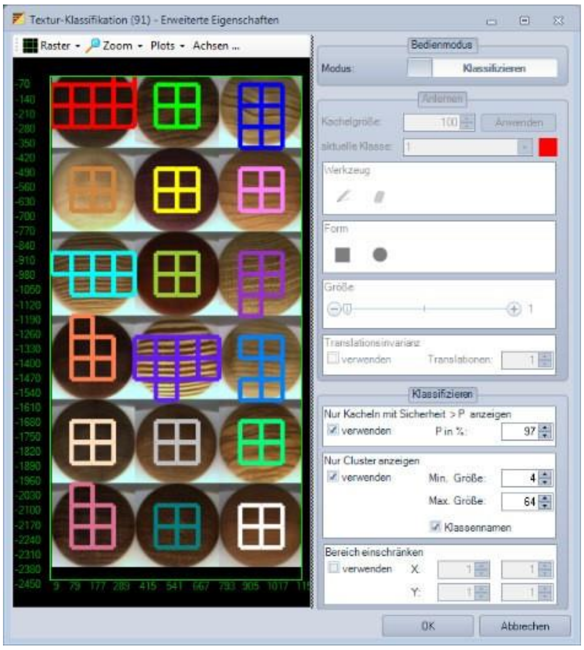

Fig.4.3. Result of the classification (18 color textures)

5 Summary

With the methods for classification described here, color textures can be reliably detected and classified in the production process independent of external parameters such as brightness, object positions (translation and rotation), object distances (scaling) or curved surfaces (rotation + scaling).

The methods described here are also suitable for reliably classifying at least 18 colour textures even if they optically differ only slightly from each other.

The online classification of color textures is a classic task in the wood, furniture and textile industry. For example, unwanted defects or partial soiling on moving webs can be reliably detected regardless of fluctuations in brightness and/or shadows during process operation.

The implementation of the methods, the triggering of the color cameras, the processing of the color information including the output of the results to the process control is done with the data analysis program Xeidana®. The following algorithm has been developed for teaching and classifying HSI color textures is inserted:

a) Teach-in phase of the objects
   1. RGB-HSI transformation of the color textures
   2. set fewer segments on the color textures of each class with e.g. 24x24Pixel
   3. suitable transformations {HSI}, e.g. 2D-FFT for formation characteristic 2D spectral mountains in these segments

4. extraction of statistical features from the 2D spectral mountains
5. setting up the individual classifiers

b) Identification & classification in process operation
1. RGB-HSI transformation of all pixel values of the image
2. segmentation of previously defined areas of the image (ROI)
3. suitable transformations {HSI} of all segments
4. extraction of statistical characteristics
5. robust classification

References

1. Beyerer, H., Heintz, R.: Licht und Farbe. In: Fraunhofer Allianz Vision Seminar Inspektion und Charakterisierung von Oberflächen mit Bildverarbeitung, Erlangen (Dec. 2007).
2. Matile, H.: Die Farbenlehre Phillip Otto Runges, 2nd edn. München (1979).
3. 3 https://www.iwu.fraunhofer.de, last accessed 2020.
4. Mende, M., Wiener, T.: Online-Klassifikation von Farbtexturen. In: Fraunhofer Vision Leitfaden 16 "Inspektion und Charakterisierung von Oberflächen mit Bildverarbeitung", pp.66. (2016).
5. Mäenpää, Topi.: The local binary pattern approach to texture analysis – extensions
6. and applications. In: Infotech Oulu and Department of Electrical and Information Engineering, University of Oulu, P.O.Box 4500, FIN-90014 University of Oulu, Finland Oulu, Finland (2003).
7. Priber, U., Kretzschmar, W.: Inspection and Supervision by Means of Hierarchical Fuzzy Classifiers. Fuzzy Sets and Systems, Vol. 85/1, North-Holland (1997).
8. Vapnik, Chervonenkis: Theory of Pattern Recognition (1974) (germ.: Wapnik und Tschervonenkis, Theorie der Mustererkennung (1979).
9. Schölkopf, Smola: „Learning with Kernels”, MIT Press (2001).
10. Duda, Richard O., Hart, Peter E., Stork, David G., Pattern Classification. 2nd edn. Wiley Interscience ISBN 0471056693 (2000).