Rapid Classification of Textile Fabrics Arranged in Piles

Dirk Siegmund, Olga Kaehm and David Handtke
Fraunhofer Institute for Computer Graphics Research (IGD), Fraunhoferstrasse 5 64283, Darmstadt, Germany

Keywords: Quality Assurance, Textile Fabrics, Pattern Recognition, Textile Classification.

Abstract: Research on the quality assurance of textiles has been a subject of much interest, particularly in relation to defect detection and the classification of woven fibers. Known systems require the fabric to be flat and spread-out on 2D surfaces in order for it to be classified. Unlike other systems, this system is able to classify textiles when they are presented in piles and in assembly-line like environments. Technical approaches have been selected under the aspects of speed and accuracy using 2D camera image data. A patch-based solution was chosen using an entropy-based pre-selection of small image patches. Interest points as well as texture descriptors combined with principle component analysis were part of this evaluation. The results showed that a classification of image patches resulted in less computational cost but reduced accuracy by 3.67%.

1 INTRODUCTION

The cleaning of textiles in manufacturing industry is nowadays an often completely automatized task operated by machines. Nevertheless the visual quality assurance after washing and drying is mostly manually operated by humans. Fabric in textiles can include cotton, wool, polyester or a composite of them. As human errors occur due to fatigue, an automated inspection can improve quality and reduce labor costs. In traditional textile manufacturing, fabric is inspected during the furling process and can be considered as a continuous 2D texture. However, this work deals with pieces of textiles on assembly-line like environments. As there is no mechanical solution for spreading the textiles in an automatized way, the items will be inspected in a pile-like arrangement. Discontinuous surfaces in combination with varying colors and weaving of different textile fibers are some of the challenges in this task. When dealing with recurring items, the recognition of the item type is an important aspect to guarantee sorting accuracy. In this work four woven cotton textiles each with different fabrics were used as experimental objects. As high processing speed is required, this work will focus on 2D methods for fabric classification. The previous research results in fabric classification were carried out on spread fabrics and required a 2D patterned texture defined by an underlying lattice with symmetric properties. Unlike other projects this work examines the applicability of the visual descriptors LBP (Local Binary Pattern) and SURF (Speeded Up Robust Features) in combination with the common classifiers SVM (Support Vector Machine) and Adaboost. All approaches were applied on the full image as well as on cropped patches of smaller size. The database consists of 537 images from 196 different textiles of four different fabrics (= textile types). As the textile comes in used condition the type of textile is not the only property in the quality assurance. Some images of textiles therefore have dirt, holes or other defects, like the ones defined by the textile industry (Council, 2000). Because some textiles may have been washed many times, the fiber textile may also look different in color and appearance. There are techniques for textile classification that can differentiate between fabrics with up to 98% (Ngan et al., 2011) (Rebhi et al., 2015) (Abou-Taleb and Sallam, 2008) accuracy. These existing approaches require the texture surface to be a flat and spread-out 2D surface. In quality assurance after washing and drying this is not the case. The textiles are in a voluminous shape and show folds, edges, and borders. Folds as well as overlapping borders have a negative impact on the correct fabric classification. The three dimensional shape tends to influences the size of the weaving in the image. This work will examine how the chosen visual 2D descriptors and classifiers perform on these textiles in a verification scenario and will close with a conclusion and outlook for future investigation.

Siegmund, D., Kaehm, O. and Handtke, D.
Rapid Classification of Textile Fabrics Arranged in Piles.
DOI: 10.5220/0005969300990105
In *Proceedings of the 13th International Joint Conference on e-Business and Telecommunications (ICETE 2016) - Volume 5: SIGMAP*, pages 99-105
ISBN: 978-989-758-196-0

Figure 1: Textile in pile-like arrangement.

2 RELATED WORK

All found previous research work in fabric classification was done on spreaded fabrics. Some approaches utilized Artificial Neural Networks (ANN) like Kang and Kim (Kang and Kim, 2002) who involved a trained ANN for color grading of raw cotton. The images were captured by a color CCD camera with which they acquired color parameters, checked connectivity and evaluated trash particles for their content, size, distribution and spatial density with a high recognition rate compared to other methods. She et al. (F.H. She and Kouzani, 2002) classified two kinds of animal fibers objectively between merino and mohair. In their approach they developed a system that uses an ANN and image processing for this classification. Kuo and Lee (Kuo and Lee, 2003) developed a system to distinguish defects of fabrics like holes, oil stains, warp-lacking, and weft-lacking. For that reason they used a back-propagation Neural Network which gets an image as input. They successfully determined nonlinear properties and improved the recognition. Srikaew et al. (A. Srikaew and Kidsang, 2011) presented a hybrid application of gabor filter and two-dimensional principal component analysis (2DPCA) for automatic defect detection of texture fabric images. With a Genetic Algorithm based on the non-defect fabric images they achieved the optimal network parameters. With their experiments they concluded that the applied gabor filters efficiently provide a straight-forward and effective method for defect detection by using a small number of training images but still can generally handle fabric images with complex textile pattern background. Another approach from Sun and Zhou (Sun and Zhou, 2011) used a threshold segmentation method to identify if there are any defects existed in the fabric. They adopted an image feature based approach to recognize oil stain and holes, and used training based technique to detect broken ends and missing picks. They segmented and filtered the defect image, extracted features of the fabric defect, the classification was based on local features and training. For automated visual inspection Ngan et al. (H.Y.T. Ngan and Ng, 2005) used a wavelet transformation based approach. With direct thresholding (DT) and a so-called golden image subtraction method (GIS) they segmented out the defective regions on patterned fabric effectively. They also present a comparison with other methods. To address the 3D shape of the textile in the task presented here, this work uses the general pattern descriptor LBP and rotation and scale invariant local features.

3 APPROACH

3.1 System Overview

The method presented in this work consists of: segmentation, patch extraction, pre-selection, feature extraction, classification and fusion. The individual steps of the process are shown as a pipeline in Figure 2. The system has been evaluated including and excluding the steps: patch extraction and pre-selection. For feature extraction the local interest point descriptor SURF, as well as the LBP descriptor were used. In the classification process the classifiers SVM and AdaBoost were evaluated. When using patches instead of the full image, these patches were preselected using the Shannon Entropy Value. The results of the classification are fused in the Decision-Level-Fusion step.

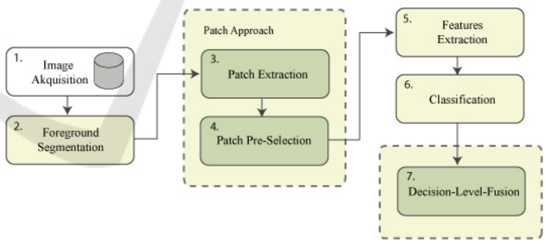

Figure 2: Program flow diagram.

3.2 Description of Methods Used

For visual distinction of the cloth quality between the types examined in this study (see Figure 3 and 4) the weaving of the textile is arranged differently and can therefore be used as property. The cloth fabric can be visually differentiated by its fineness, yarn density and its total mixture. When there are pile-like, uncontrolled arrangement of textiles on the assembly line, other properties than the fabric weaving are not always visible. The weaving pattern was therefore used as a feature for classification. However, the evaluation of this property requires a high recording quality and a correspondingly high resolution. For this reason screen tests were conducted to determine the minimal resolution with enough features to distinguish the different types of fabric. Therefore, the cloth has been divided into patches and was examined by humans on their distinctness. The tests have shown that a resolution of 4288x2848 pixels (aspect ratio of 4:3) within a receiving area of 30x40cm is optimal. Using the analysis of texture-spectrum or interest-points based features, these discriminative properties can be evaluated for a selection. To perform a classification based on the texture of the images, different approaches were examined. These can be differentiated by the used image parts, the features used and the classifier. Two different image input data formats were investigated. First the use of the full images in high resolution of 4288x2848 pixels, secondly extracted parts of the image represented in patches of the size 128x128 pixels. The idea behind using patches instead of the full image relies on the assumption that pre-selecting image parts which stores more discriminative information than others will provide a more reliable classification.

3.3 Image Acquisition

To protect the laboratory image acquisition process from light entering from the outside, a black box was used. On the inner side of the black box, black molton was attached to protect the fabric from reflection of the box. A uniform sheet of green foam rubber was used as an underlay in order to simplify separation of foreground and background in the segmentation process. For a homogeneous illumination a LED ring light with 1950 lx was used.

For image recording a camera with a CMOS DX sensor and 35mm lens was used. In Table 1 you can find a detailed description of the parameters used. All test objects were recorded in three different pile-like arrangements. The used data format is JPEG with a low compression rate.

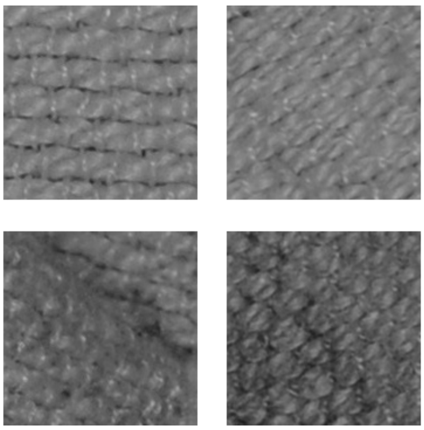

Figure 3: Examined patches of textiles (left column: type 1, right column: type 2).

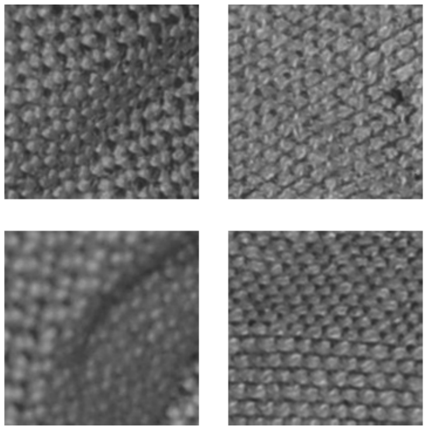

Figure 4: Examined patches of textiles (left column: type 3, right column: type 4.)

Table 1: Camera parameters.

Parameter	Property
Resolution	4288x2848 pixels
Focal Length	35mm
Sensor	CMOS 23,6mm x 15,8mm
Aperture	F8
Exposure	1/200s

3.4 Database

The database consists of 537 images from 196 different textiles of four different fabrics (= textile types). As the weaving properties are the only used distinguishing feature, the quality varies in the parameter of yarn density and fineness. The yarn density reaches from 9.5x6.5 fibers/cm for the most rough fabric to 26x16 fibers/cm for the finest one. The fineness of the fibers lies in the range of 50/2 Nm x 5.2/2 Nn to 200/2 Nm x 80/2Nm. The examined textiles were in cleaned and dry condition when they were recorded. Nevertheless their condition varies a lot because some of them are worn out. Most textiles show therefore dirt, holes or others defects. Furthermore, every textile has one out of three different colors. To classify the fabrics based on their different characteristics the ground truth was manually determined by visual inspection. Table 2 gives an overview of the quantities of examined textiles in the database. The yarn density and fineness is increasing with the type of textile weaving used. This is shown in Figures 3 and 4. Furthermore, each type of textile can have one out of three colors.

Table 2: Quantities of examined textile images in the database (full image).

Type	#Images (#defect)	#Color1/Color2/Color3
1	186(165)	87/48/51
2	177 (140)	69/66/42
3	144 (120)	66/54/24
4	30 (13)	12/3/15

3.5 Preprocessing

In the segmentation step (see Figure 2 step 2) the background is separated from the foreground by using a mask. The image was first converted into the HSV color space. A color range for the 'H' (hue) value was used to define the background color as lying between `lowerH` and `upperH`. Pixel in mask(I) are set to 255 if src(I) is within the specified range and 0 otherwise.

$$\mathtt{mask}(I) = \mathtt{lowerH}(I)_0 \leq \mathtt{src}(I)_0 \leq \mathtt{upperH}(I)_0 \quad (1)$$

The mask was inverted and then applied onto the source image. The morphological operators erosion and dilation were used to exclude remaining smaller artifacts in the background from the foreground. In the patch extraction (see Figure 2 step 3) the images were splited into patches with the size of 128x128 pixels.

3.6 Pre-selection

In this approach, a entropy value was determined which was used to characterizes the image quality. Unlike a training based approach the decision was made using a single value. The pre-selection was therefore based on a threshold value. The so-called Shannon Entropy Value is a value that measures the information content in data and cam be used as a measure of image quality. Based on that, an approach for patch selection is applied to choose the patch with higher entropy, i.e. higher quality and information content. The entropy of a patch I is calculated here by summing up the entropy of each of the three channels of the image. The entropy of each image channel is the sum of all pixel values probability $p(i)$ multiplied by log_2 of those probabilities. The probability of a pixel value $p(i)$ is obtained by calculating a normalized histogram of the possible pixel values (here, $i = \{1, \ldots, 2^8\}$). The entropy of a 3-channel, 8-bit image can be formulated as:

$$E(I) = -\sum_{C=1}^{C=3} \sum_{i=1}^{i=2^8} p(i) \log_2 (p(i)) \quad (2)$$

The entropy values of all patches were calculated and a number of patches with the highest entropy values selected for further processing. The number of seven patches with the highest values were considered as adequate in order to guarantee constant computational costs. It was furthermore observed that at least seven patches with values higher than the threshold could be found in every image. Patches with lower entropy values tended to show a higher error-rate.

3.7 Feature Extraction

In feature extraction, the image is assigned to a class representing a textile fabric (see Figure 5). In the approach using patches, all divided image patches describe one single class. The well-known SURF features (Bay et al., 2006) have shown their effectiveness in many recent papers dealing with object recognition tasks (Yang et al., 2007). SURF Features are scale-invariant and robust against rotation, translation and changing lightning conditions. Therefore they are applicable for the detection of invariant features. Before feature extraction, images were converted into a gray-scale representation and histogram equalization was applied. A set of interest points was extracted using the fast hessian detector. The kind of extracted feature points was specified using manually selected library of 120 images. These features were further processed within a 'bag of words' approach using a 64-dimensional vector as a descriptor. The size of the dictionary was examined by evaluating the overall performance for different dictionary sizes with the same trainings and test sets.

Local Binary Patterns (LBP) are used to analyze texture spectra and are often used for classification in computer vision task. Its strength is its extreme tolerance towards brightness changes, since only the local gray value changes are considered. Local Binary Patterns represent the local structure of an image and are invariant to monotonic changes of the brightness. They have been applied on different tasks the field of image recognition (Luo et al., 2013) and achieved high detection rates(Wang et al., 2009). A darkening of the image (e.g. in case of shadows occurring in folds of the textile) has therefore no negative influence to the feature vector. After gray-scale conversion and histogram equalization the image was divided into blocks of 16x16 pixels, which resulted in 64 blocks per patch or 47,704 blocks for the full image. To each pixel of the gray-scale image (except marginal areas) was assigned a new 8-bit value. This value was calculated from 8 neighboring pixels of the current pixel:

$$LBP = \sum_{n=0}^{7} s\,(i_n - i_c) \cdot 2^n \quad (3)$$

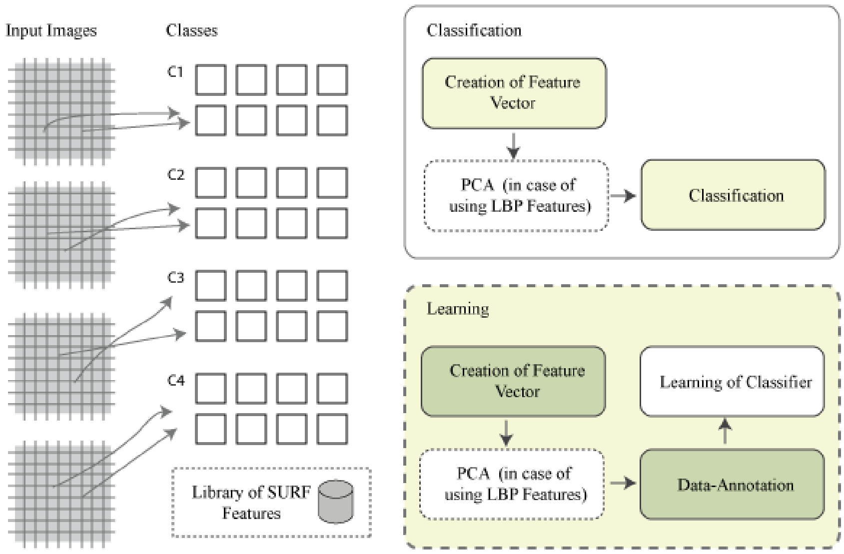

Figure 5: The left part illustrates the assignment of patches to classes based on their entropy value, the right part shows the feature extraction, training and classification process.

For the center pixel, i_c is the gray value of the pixel in the gray values of adjacent pixels (continuously starting left above the center pixel and then clockwise). For each block, a normalized histogram is calculated using the number of uniform pattern as bins. The histograms of each block were concatenated to a feature vector. PCA (Principal Component Analysis) was performed on that feature vector to reduce the dimensionality. As a part of it, eigenvalues, eigenvectors and mean were calculated from a subset of the database. By using PCA the number of components in the feature vector was reduced by 92.03% from 3,766 to 300 in the approach using patched. For the full image the number of components was reduced from 2,766,832 using the same percentage of reduction. The resulting feature vectors were used in five fold cross validation for training and prediction.

3.8 Classification

The image classification in one of the core components of the recognition process. The used machine learning approach requires learning a classifier. Changes in the previous steps can have a high impact on the recognition results. The previously described features are stored as feature vectors F : $F = f_1, f_2, f_3, \ldots, f_7$ in the patch based approach. In the image based approach only one feature vector is used. For further processing all feature vectors were annotated manually and stored in form of a matrix. The four classes C1-C4 (see Figure 5) representing the four different textiles were used in the identification scenario. In the verification scenario only two classes were used in a one versus all classification approach. One representing a certain textile type (class 1) and another represents all other classes (class n). For classification of the resulting feature vectors the classifiers AdaBoost and SVM(Chang and Lin, 2011) were used for supervised learning. In case of SVM classification, C-Support Vector Classification which allows imperfect separation of classes with penalty multiplier and radial basis function was used. AdaBoost combines the performance of many 'weak' decision tree classifiers to produce a powerful committee(Hastie et al., 2005). The AdaBoost variante 'Gentle'(Friedman et al., 2000) was choosen because it puts less weight on outlier data and was therefore expected to work better with images of defect textiles. Five fold cross validation folders were used to verify the classification results. In the approach using patches instead of the full image, only a number of patches with the highest entropy value were used to create the cross validation folds. This is reasoned because it was expected that patches with a higher information value show a lower error rate. It was furthermore expected that this approach saves computational costs. The scores of all patches that belong to one textile were fused using mean-rule fusion-rule. Verification and identification scenarios have been evaluated.

4 RESULTS AND EXPERIMENTS

The identification scenario was evaluated with a qualitative selection of image patches (patches), as well as without such a pre-selection (full-image). The pre-selection was thereby done using the Shannon-entropy value. The accuracy indicates the successful differentiation between the 4 classes (True Positive Rate). It was tested against a data set of 537 images. The images were equally distributed over five subsets. For each training of a classifier four subsets were used for training and one for testing. The results in identification show that the approach using patches resulted in a weaker performance compared to the one using the full image. The SURF interest point features in a Bag of Words (BOW) approach showed a better performance than LBP feature. This may reasoned in their scale and rotation invariant characteristic. In the verification scenario the same data set was used as for the identification scenario. As SVM and SURF outerperformed the AdaBoost classifier by an average of 3.67% accuracy, the verification results are only shown for the SVM classifier and SURF features. The results show clearly better accuracy for all textile types and a difference of only 2.89% accuracy between the patch based approach and the approach using the full image was obtained. A possible reason for the poor performance of the approach with pre-selection of pieces of cloth is caused by the kind of information excluded by the algorithm. It can be seen that discriminative information is stored in even patches with lower entropy. The speed of the algorithm using SURF features on image patches on an Intel Core i7 4770 is 503ms. The approach using the full image instead of patches is 923ms.

Table 3: Classification accuracy in identification scenario.

Image Size	Feature	Classifier	Accuracy
Full Image	LBP/PCA	SVM	65.52%
Full Image	SURF(BOW)	SVM	86.43%
Patches	LBP/PCA	SVM	59.9%
Patches	SURF(BOW)	SVM	85.41%
Full Image	LBP/PCA	AdaBoost	63.96%
Full Image	SURF (BOW)	AdaBoost	82.10%
Patches	LBP/PCA	AdaBoost	59.72%
Patches	SURF (BOW)	AdaBoost	80.33%

5 CONCLUSION

In this work, fabric patterns were classified using a database of textiles in a pile-like arrangement. There are multiple steps for classifying the fabrics: one involves extracting the features of woven fabric images, the other involves recognizing the class of woven fabrics. In order to find a solution which takes into account speed and accuracy, an approach which used patches instead of the full image was decided upon. Interest points as well as texture analysis based features were deployed and evaluated using different classifiers. For both identification and verification, the interest point based descriptor, SURF (in combination with bag of words and the SVM classifier), demonstrated the best performance. The patch-based approach reduced the calculation costs needed for prediction by 46% while showing reduced 3.67% less accuracy the verification. With the development of further methods, the image automatic identification and classification of woven fabrics could promote the development of the textile industry.

Table 4: Classification accuracy in verification scenario using SVM.

Image Size	Type	Feature	Accuracy
Full Image	1	SURF (BOW)	94.68%
Full Image	2	SURF (BOW)	89.91%
Full Image	3	SURF (BOW)	96.56%
Full Image	4	SURF (BOW)	94.96%
Patches	1	SURF (BOW)	90.01%
Patches	2	SURF (BOW)	89.26%
Patches	3	SURF (BOW)	92.14%
Patches	4	SURF (BOW)	94.95%

REFERENCES

A. Srikaew, K. Attakitmongcol, P. K. and Kidsang, W. (2011). Detection of defect in textile fabrics using optimal gabor wavelet network and two-dimensional pca. In *Advances in Visual Computing*, pages 436–445. Springer.

Abou-Taleb, H. A. and Sallam, A. T. M. (2008). On-line fabric defect detection and full control in a circular knitting machine. *AUTEX Research Journal*, 8(1).

Bay, H., Tuytelaars, T., and Van Gool, L. (2006). Surf: Speeded up robust features. In *Computer vision–ECCV 2006*, pages 404–417. Springer.

Chang, C.-C. and Lin, C.-J. (2011). Libsvm: a library for support vector machines. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 2(3):27.

Council, H. K. P. (2000). *Textile Handbook 2000*. The Hong Kong Cotton Spinners Association.

F.H. She, L.X. Kong, S. and Kouzani, A. (2002). Intelligent animal fiber classification with artificial neural networks. *Textile research journal*, 72(7):594–600.

Friedman, J., Hastie, T., Tibshirani, R., et al. (2000). Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors). *The annals of statistics*, 28(2):337–407.

Hastie, T., Tibshirani, R., Friedman, J., and Franklin, J. (2005). The elements of statistical learning: data mining, inference and prediction. *The Mathematical Intelligencer*, 27(2):83–85.

H.Y.T. Ngan, G.K.H. Pang, S. Y. and Ng, M. (2005). Wavelet based methods on patterned fabric defect detection. *Pattern recognition*, 38(4):559–576.

Kang, T. J. and Kim, S. (2002). Objective evaluation of the trash and color of raw cotton by image processing and neural network. *Textile Research Journal*, 72(9):776–782.

Kuo, C.-F. J. and Lee, C.-J. (2003). A back-propagation neural network for recognizing fabric defects. *Textile Research Journal*, 73(2):147–151.

Luo, Y., Wu, C.-m., and Zhang, Y. (2013). Facial expression recognition based on fusion feature of pca and lbp with svm. *Optik-International Journal for Light and Electron Optics*, 124(17):2767–2770.

Ngan, H. Y., Pang, G. K., and Yung, N. H. (2011). Automated fabric defect detectiona review. *Image and Vision Computing*, 29(7):442 – 458.

Rebhi, A., Benmhammed, I., Abid, S., and Fnaiech, F. (2015). Fabric defect detection using local homogeneity analysis and neural network. *Journal of Photonics*, 2015.

Sun, J. and Zhou, Z. (2011). Fabric defect detection based on computer vision. In *Artificial Intelligence and Computational Intelligence*, pages 86–91. Springer.

Wang, X., Han, T. X., and Yan, S. (2009). An hog-lbp human detector with partial occlusion handling. In *Computer Vision, 2009 IEEE 12th International Conference on*, pages 32–39. IEEE.

Yang, J., Jiang, Y.-G., Hauptmann, A. G., and Ngo, C.-W. (2007). Evaluating bag-of-visual-words representations in scene classification. In *Proceedings of the international workshop on Workshop on multimedia information retrieval*, pages 197–206. ACM.