Identification of Leather Surface Defects using Fuzzy Logic

Kaloyan Krastev, Lidiya Georgieva

Abstract: *In the present work an application of fuzzy logic for leather surface defects identification is investigated. The defects create a discontinuity at the surface which leads to regions with different intensities than the background. Binary images are obtained after the segmentation. They contain non-defective (regular texture) and defective structural elements. The objective is to classify the elements and to detect the defective ones. This is done by applying a fuzzy logic technique as the application of different Rule Bases and different numbers of output linguistic terms are investigated.*
Key words: *Leather, Leather Surface Defect, Fuzzy Logic, Fuzzy Rule Base.*

INTRODUCTION

A major factor in the leather quality estimation process is the presence of surface defects. They create a discontinuity at the surface which leads to regions with different intensities (grey levels) than the background during the image acquisition, and can be identified by using digital image processing techniques.

In [8] multiresolution pyramids have been used for the construction of a leather surface texture model. An autoregressive rotation invariant model is used to obtain the pyramid's parameters. This methodology has been applied for detection of the skin disease defects (hypodermatosis) in calf leather. The disadvantage of the method is its incapability to segment smaller size objects.

A reference standard of leather defect compensation is proposed in [9]. Seven types of defects are defined depending on their size and shape and the most usual causes for every type are noticed. A histogram based method is used for detection of the defects and a grouping algorithm for nearby fault regions is applied. The established compensatory standard is reliable and effective, but the defect detection and classification process is not fully automatic.

In [5] a machine-vision-based approach for grading leather hides is developed. A specially designed machine vision system is used for the image acquisition and combined edge detector and a statistical and texture learning approach has been applied for the defects extraction. Cuttable area estimation algorithm is included at the final stage of the proposed methodology to rank the leather samples.

An automated vision system for detecting and classifying of surface defects on leather fabric is proposed in [7]. A two-step segmentation procedure based on thresholding and morphological operations has been performed. Normalized compactness measure and first- and second-order statistical features have been used for the classification of the defects in five different classes.

Perspective techniques for image segmentation and objects classification are fuzzy rule based approaches. In [3] a cork quality classification system has been developed. Morphological filtering and contour extraction and following (CEF) have been used as feature extraction method and a fuzzy-neural network as defects classifier. In [2] an unsupervised texture separation algorithm is discussed. Multiscale fuzzy gradient operator has been applied to generate a multichannel image from which the boundaries between the homogeneous textured regions have been extracted. In [4] an approach for fuzzy-based unsupervised segmentation of textured color images is proposed. L*a*b color space and statistical geometrical features have been used for texture description. Fuzzy-based homogeneity decision has been performed for hierarchical image segmentation. In [1] a neuro-fuzzy approach for classification of image pixels in three classes is presented: contour, regular and texture points. The fuzzy rule base is automatically defined via a two step learning of the neuro-fuzzy network, performed over a training set of available data.

The present work deals with the identification of leather surface defects using fuzzy logic. The objective is to develop and investigate appropriate fuzzy-based system for defects identification.

IMAGE SEGMENTATION AND FUZZY BASED DEFECTS IDENTIFICATION.

Image segmentation.

In the previous work [6] a structural image segmentation methodology has been proposed. The main steps of the methodology are shown on fig. 1:

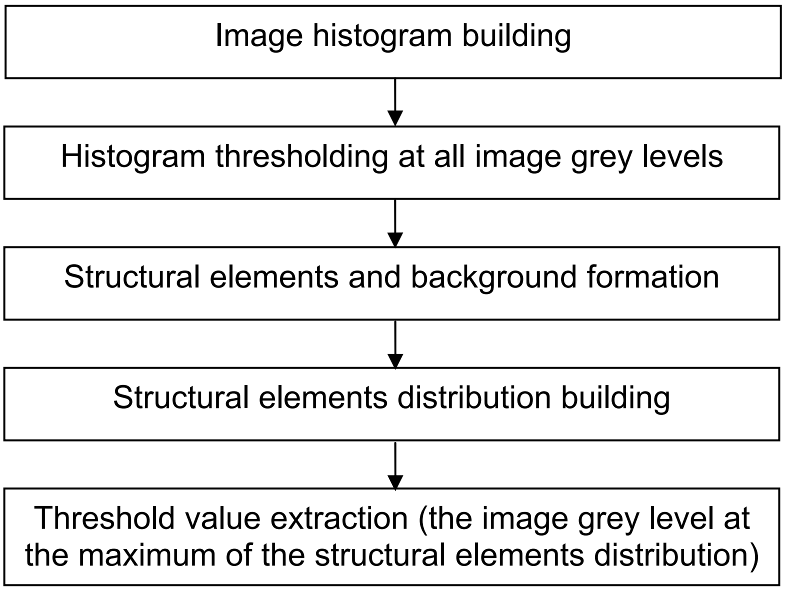
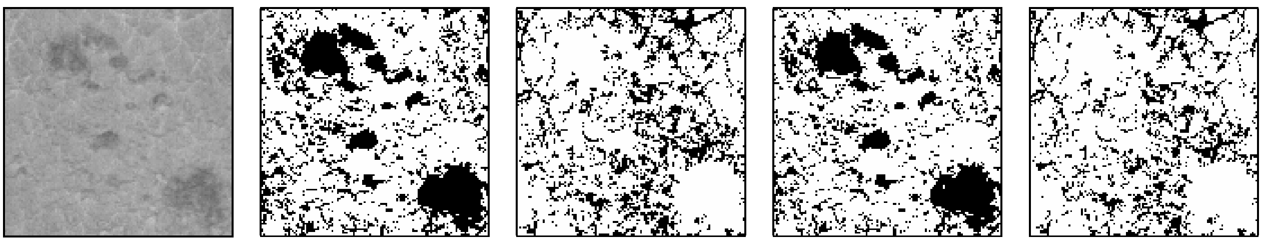


Fig. 1. Leather image segmentation methodology.

As a result of the application of this methodology, four binary images are obtained (fig.2) – for the left and the right end of the histogram (corresponding to darker and lighter objects in the image) about 4- and 8-connected pixels. The object of the present work is only to identify the surface defects, i.e. to classify the structural elements as defective or non-defective. That is why only one of the four binary images is used further in the research (left end and 4-connected pixels) – the rest will produce similar results.



a) b) c) d) e)

Fig. 2. a) A leather sample with defects; b), c), d), e) Segmented binary images for the left histogram's end and 4-connected pixels, the right end and 4-connected pixels, the left end and 8-connected and the right end and 8-connected pixels respectively.

Generating the membership function to the antecedent and their Linguistic Terms (LTs).

As it is shown on fig. 2 the segmented leather images contain non-defective (regular texture) and defective structural elements. A feature which can distinguish these two classes is the area of the elements. Usually defective ones have bigger area than the regular ones. The area can be measured as the number of pixels contained in a structural element.

Another useful feature could be the distance between the image threshold grey levels obtained at the segmentation stage and the mean intensity of the segmented objects (fig.3). The object is more likely to be defective when the distance is big and to be a regular texture element when the distance is small.

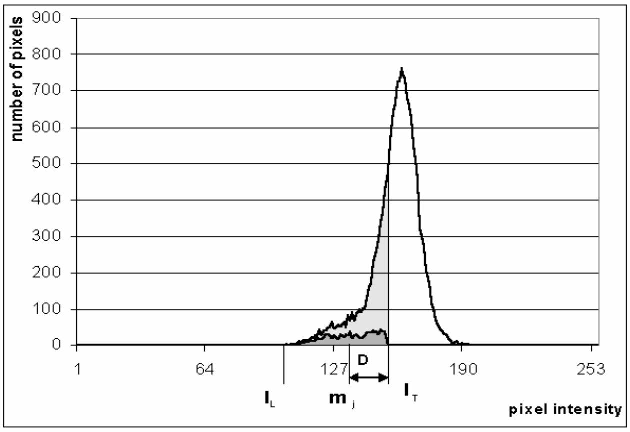


Fig. 3. The distance measure.

In the present work the normalized distance measure is used:

$$D_j = \frac{|I_T - m_j|}{|I_T - I_L|}, \tag{1}$$

where I_T is the image threshold grey level, I_L – the histogram's lowest grey level (left end), m_j – the mean intensity of the segmented objects, j = 1,2,…,N (N – the total number of segmented objects).

The two above described features define the linguistic variables (LVs) Area (a) and Distance (dis). Three linguistic terms (LTs) are used for both variables: Small (S), Medium (M) and Big (B). The form of the linguistic term M is triangular, whereas it is trapezoidal for S and B. It is shown on fig.4:

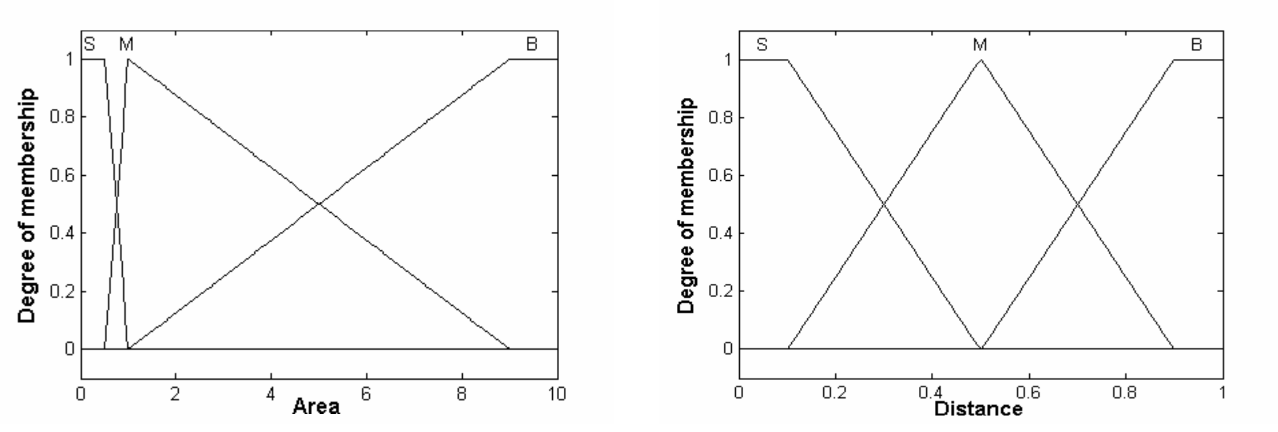


Fig. 4. The Area and Distance LVs and their LTs.

The LT Medium for the LV Area is chosen to be nonsymmetrical triangular. On the basis of the leather defects classification proposed in [9] as a characteristic area value was accepted 1 mm^2. The objects in the segmented binary images with area smaller than 1 mm^2 mainly belong to the regular texture, but some of them are defects. To detect this defects bigger sensitivity is needed which is provided by the left arm of the LT – small changes in the area will produce bigger alteration in the result. The objects with area bigger than 1 mm^2 are few in number and they could be classify as Medium in wider range.

Construction of the membership functions to the consequent and fuzzy inference rules.

The consequent in the fuzzy inference (the output LV) is the term "defect". The training set of images is used to receive appropriate Rule Base. For each one of the ordered pairs of states it is possible to determine a defect type. The two cases are investigated depend on the number of the output LTs – with 3 and 5 output linguistic terms. They are shown on fig.5 (ND – Not Defect, PND – Probably Not Defect, PD – Probably Defect, VPD – Very Probably Defect, D – Defect). The middle LTs have symmetrical triangular form while ND and D linguistic terms – trapezoidal form.

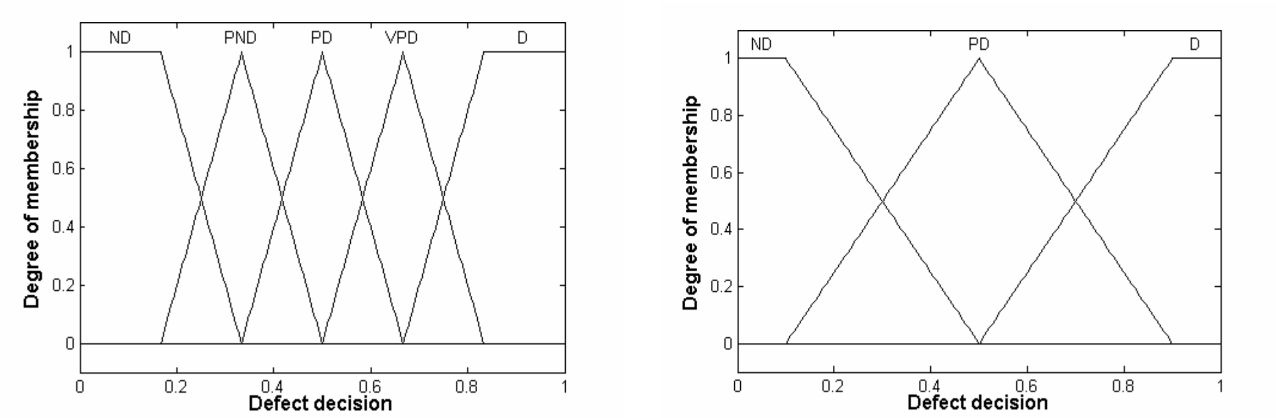


Fig. 5. The sets of LTs of the output LV.

For the two cases that are investigated (using 5 and 3 output LTs respectively) the next Rule Bases are applied – shown in Table 1 and Table 2.

Table 1

	RB1	Distance			RB2	Distance		
		S	**M**	**B**		**S**	**M**	**B**
Area	**S**	ND	PND	PD	**S**	ND	PND	PD
	M	PD	VPD	D	**M**	PD	PD	VPD
	B	VPD	D	D	**B**	VPD	D	D

Table2

	RB3	Distance			RB4	Distance		
		S	**M**	**B**		**S**	**M**	**B**
Area	**S**	ND	PD	D	**S**	ND	ND	PD
	M	PD	PD	D	**M**	ND	PD	D
	B	PD	D	D	**B**	PD	D	D

The fuzzy inference engine.

The MAX-MIN, MAX-PROD and SUM-PROD inferences are used for the evaluation of the Rule Bases. It is done by means of following operators:

- connectors inside the antecedent: AND→MIN/PROD and OR→MAX/SUM;
- conclusion: AND applied to the activated output LT→MIN/PROD;
- aggregation of the rules - OR→ MAX/SUM;

The result evaluation is based on the next algorithm for an aggregations treatment:

- connectors inside the antecedent : AND→MIN;
- conclusion: MIN applied to the activated output LT;
- aggregation of the rules – MAX.

The result is shown in (2), for MAX-MIN operator:

$$\mu^0_{DEF\,\mathrm{Res}}(\hat{def}) = \mu^0_{DEF}(\hat{def}) =$$

$$= MAX(MIN(\mu_{aLT_i}(a_j), \mu_{disLK_k}(dis_l), \mu_{defLT_m}(\hat{def})), MIN(\mu_{aLT_n}(a_j), \mu_{disLT_p}(dis_l), \mu_{defLT_q}(\hat{def}))) \qquad (2)$$

for $\forall$ *def* $\in$ *DEF*,

where *def* is the term "defect" and it is one element from the *DEF* set (defect).

Defuzzification.

There are various defuzzification methods. The choice of defuzzification method depends on the precision of the result. The most common is the center of gravity defuzzification method (CGM). The Watanabe method is often applied in practice in different versions. The output value is determined applying weights to all activated rules at definite input variables (Area and Distance).

Let the R_i and R_j rules are activated and the output variable has membership functions μ^0_{Ui} and μ^0_{Uj} for them. The rules are aggregated with an OR operator and the result is as follows:

$$def_0 = \frac{\int def.\mu^0_{DEF\,\mathrm{Res}}(\hat{def})d(def)}{\int \mu^0_{DEF\,\mathrm{Res}}(\hat{def})d(def)}. \qquad (3)$$

Experimental results.

The training set of leather images was used to obtain the experimental results of the present research. The size of the images is 128x128 pixels and they represent different types of leather with different types of defects. For all samples in the training set the proposed methodology is applied. From the results some conclusions could be made.

The differences between the output values calculated with the investigated inference evaluation operators are insignificant. The comparison of the maximal differences values for one of the samples is given in Table 3 where the four Rule Bases are used. Therefore in the future work only one inference evaluation operator will be use.

Table 3

Compared operators	Rule Base 1	Rule Base 2	Rule Base 3	Rule Base 4
max-min with *max-prod*	0.053	0.047	0.032	0.027
max-min with *sum-prod*	0.038	0.061	0.031	0.068
max-prod with *sum-prod*	0.021	0.034	0.025	0.078

Other aspect of the present work is the investigation of the correctness of the leather surface defects identification using different Rule Bases (RB). From the proposed above RBs (Table 1 and Table 2) the best results are obtained utilize RB2 and RB4 and the worst is the result in case of RB1. Therefore it may be concluded that having only 3 output LTs is enough for the correct identification of the defects.

Finding the optimal number and form of the LTs and the most appropriate Rule Base is a direction for further investigations.

CONCLUSIONS AND FUTURE WORK

In the present work a fuzzy-based approach for identification of leather surface defects is proposed. From the investigation the following conclusions could be summarized:

1. Fuzzy-based leather defects identification can distinguish the defects from the non-defective elements (regular texture);
2. The investigated input linguistic variables (Area and Distance) provide reliable measure for describing the structural elements;
3. Four Rule Bases are discussed with different results. Two of them show better identification of leather surface defects;
4. By using different inference evaluation operators (MAX-MIN, MAX-PROD, SUM-PROD) there are no significant differences in the output results of the proposed fuzzy system;

The following problems can be notice as directions for future work: improvement of the segmentation algorithm for obtaining the binary images; optimization of the rule bases, the number and the form of the linguistic terms; applying intensification (Zadeh) and others operators at the linguistic terms; investigation of new input linguistic variables (features) for better describing the defects.

REFERENCES

[1] Castiello C., G. Castellano, L. Caponetti, A. Fanelli. Fuzzy Classification of Image Pixels. Proceedings of the 2003 IEEE International Symposium on Intelligent Signal Processing (WISP2003), pp. 79-82, 2003.

[2] Ceccarelli M., A. Petrosino. A Parallel Fuzzy Scale-space Approach to the Unsupervised Texture Segmentation. Pattern Recognition Letters, 23, pp. 557-567, 2002.

[3] Chang J., G. Han, J. Valverde, C. Griswold, J. Carrillo. Cork Quality Classification System using a Unified Image Processing and Fuzzy-Neural Network Methodology. IEEE Transactions on Neural Networks, Vol. 8, №4, pp. 964-974, 1997.

[4] Dai X., J. Maeda. Fuzzy-based Unsupervised Segmentation of Textured Color Images. Proceedings of IEEE International Conference on Image Processing (ICIP 2002), pp. 293-296, 2002.

[5] Hoang K., A. Nachimuthu. Image Processing Techniques for Leather Hide Ranking in the Footwear Industry, Machine Vision and Applications, 9, pp. 119-129, 1996.

[6] Krastev K., L. Georgieva, N. Angelov. Structural Approach for Leather Surface Defects Detection. RU Annual Scientific Session, 2004.

[7] Kwak C., J. Ventura, K. Tofang-Sazi. Automated Defect Inspection and Classification of Leather Fabric. Intelligent Data Analysis, 5, pp. 355-370, 2001.

[8] Serafim A. Segmentation of Natural Images Based on Multiresolution Pyramids Linking of the Parameters of an Autoregressive Rotation Invariant Model. Application on Leather Defects Detection. Proceedings of the 11th International Conference on Pattern Recognition (IAPR 1992), pp. 41-44, 1992.

[9] Yeh C., D.-B. Perng. A Reference Standard of Defect Compensation for Leather Transactions. The International Journal of Advanced Manufacturing Technology, Online First, 2004.

ABOUT THE AUTHOR

Kaloyan Krastev, MSc, Department of Computer Systems and Technology, University of Rousse, E-mail: knedkov@ecs.ru.acad.bg.

Assoc. Prof. Lidiya Georgieva, PhD, Department of Computer Systems and Technology, University of Rousse, Phone: +359 82 888 380, E-mail: LGeorgieva@ecs.ru.acad.bg.