Grey Scale Texture Classification Method Comparison Considering Object and Lighting Rotation

Karolina Nurzyńska, Mamoru Kubo, and Ken-Ichiro Muramoto

Abstract—**This study addresses the statistical texture features as methods for texture classification. It compares its performance on two benchmark data sets: Brodatz and PID, which permit to gain better understanding how those methods deal with texture rotation and lighting changes. Moreover, few simple feature techniques are introduced in order to compare their performance with those already known (e.g. first order features, co-occurrence matrix, run length matrix, grey-tone difference matrix, local binary pattern). Finally, exploiting structures designed in methods like co-occurrence matrices as a feature vector is suggested.**

The gathered results show the correct classification ratio in range of 92-100%. However, worse performance is noticeable on data set with changing lighting conditions. Moreover, the experiments prove that the introduced simple techniques classify with similar accuracy as well as known methods. It is also interesting that exploiting the structures as feature vector proved to improve the classification results.

Additionally, due to lower classification calculation complexity the feature vectors length have been diminished with the application of principal component analysis. This experiments showed that exploiting 95% of original information considerably reduces the feature vector length and does not influence the correct classification ratio of all tested methods.

Index Terms—**Image classification, image processing, texture operators.**

I. Introduction

Each object in the surrounding world has a texture. It might be plain or coarse one, but for human eye it is a descriptive mean for object recognition. Therefore, a lot of efforts have been taken to allow exploitation of texture information in machine vision. From early beginning, the researchers dealt with this problem designing many different texture descriptors, which could be applied for segmentation [1] in image preprocessing stage or to derive the feature vectors for classification needs. There could be also distinguished many attitudes to this problem, as those methods are based on statistical information gathered in the images [2-13] model based, or exploiting texture spectrum [14], etc. The field of application is also very broad especially in medicine [15, 16]. But there are also other domains, for instance painted strokes recognition [17]. During pursuing of texture descriptive features it was noticed that finding a description invariant on any arbitrary rotation of texture or the lightning brings the solution of the problem.

In this study, the statistical texture features are addressed. The aim is to compare the invariance of well-known algorithms on texture rotation and change of the lighting condition within an image. Although, we are not only interested in comparison of the designed feature vectors described by the authors, but also we suggest exploiting the data structures as feature vectors. Additionally, very simple from the theoretical point of view and with low computational demands techniques for texture description are introduced and their performance is compared, too. Finally, the principal component analysis is exploited to remove the redundant information and limit the size of feature vectors.

II. Texture Operators

This section presents methods for image texture description. In the literature there are four main branches of texture processing methods [12]: statistical, geometrical, model based, and signal processing. This study concentrates on the statistical methods. First of all, the well-known methods are presented. However, in some cases novel approach for its application is suggested. Next, simple, local texture statistic operators are introduced. Mainly, to compare the classification efficiency between methods of different feature complexity.

A. Literature Overview

The first order features (FOF) are derived from the intensity distribution in an image. They describe the general quality of the image. Let I(x,y) represents an image function of two space variables x and y, where x = 0,...,M-1 and y = 0,...,N-1. This function can take values i = 0,...,G-1, where G represents total number of intensity levels in the image. The normalized histogram creates the base for mean, variance, skewness, kurtosis, energy, and entropy features definition recalled by Materka in [8].

Next, the second order features consider additionally the spatial relations between the luminance intensities within image. As a consequence, they contain information about the spatial properties that is important in image description.

The spatial relation has been introduced by Haralick et al. [6] in the definition of spatial dependence matrix, which later becomes called a co-occurrence matrix [13]. Generally speaking, the co-occurrence matrix (COM) stores the information about the illumination values co-appearance in image. For given G luminance levels the COM has a resolution GxG. Each cell com(i,j) contains information of co-occurrence of intensity levels of value i and j in given

Manuscript received June 11, 2012; revised July 15, 2012.

Karolina Nurzynska, Mamoru Kubo, and Ken-ichioro Muramoto are with Kanazawa University of Technology, Kakuma, Kanazawa 920-1192, Japan (e-mail: karolina.olga.nurzynska@gmial.com, kubo@et.t.kanazawa-u.ac.jp, muramoto@t.kanazawa-u.ac.jp).

DOI: 10.7763/IJCTE.2013.V5.639

direction θ at given distance d. Starting from this data structure 14 features have been described [6] and in order to assure rotation independence the final feature vector consists of its averaged values with standard deviations calculated over all directions.

It is assumed that texture of good quality is characterized by a small number of consecutive pixels of similar luminance. Run length matrix (RLM) has been proposed [5] to verify this finding. For image the run length matrix RLM(i,j) is defined as the number of runs of pixels of luminance i and length j. Where the maximal pixel value is G and the maximal run depends on the image resolution M and N. Starting from this structure description, there have been suggested many features which describe different aspects of the texture. For its equation please refer to [2, 4, 5, 11].

There were also attempts to define texture measures correlated with human perception of textures. One of the examples of such techniques is grey-tone difference matrix (GTDM) [3]. It is a vector containing G elements. Its entries are computed as the measurement of difference between intensity level of pixel and average intensity over a square, sliding the window centered at the pixel. Similarly, as in previous cases, this structure is then exploited to calculate texture describing operators like: coarseness, contrast, busyness, complexity, and texture strength.

Finally, authors of local binary patterns (LBP) [9, 10] understand texture as a two-dimensional phenomenon characterized by two orthogonal properties: spatial structure (pattern) and contrast (the ‘amount’ of local image texture). The joint distribution of grey values over a circularly symmetric neighbour set of pixels in a local neighbourhood is a starting point of the definition. Then the operator invariant against any monotonic transformation of grey scale is derived. Rotation invariance is achieved by recognizing that this grey scale invariant operator incorporates a fixed set of rotation invariant patterns. All these characteristics are calculated locally in order to summarize the texture quality in joint distribution of calculated features. The performance, however, depends on chosen parameters describing the radius of the neighbourhood and number of descriptive pixels (in this research it was 3 and 24, respectively). Moreover, usually better results are achieved when the information of LBP is supported by the information concerning local variation of data VAR.

B. Structure Based Texture Operators

In case of RLM it has been noticed [2] that instead of calculating all the parameters and creating from them the feature vector, similar results are achieved when the exploited data structure is used as a feature vector.

The descriptive property of the RLM is obvious, however the only drawback which probably restrained its creators from using it in straight forward form were its dimensions. In case of this research the number of considered grey scale values is quantized into 16 and the maximal run length is assumed 40.

Since it is possible to take advantage of RLM structure similar effects should be achieved when the basic structures created for other techniques are exploited. Therefore, in this study except of the feature vectors mentioned in previous part additionally the data structures created by the methods are also used for texture description. That results in two novel feature vectors based on following structures:

1) co-occurrence matrix calculated for images with quantized illuminance into 16 values and
2) grey-tone difference matrix achieved for original images of 256 grey shades.

Moreover, the normalized histogram (NH) of 64 bins is also regarded as a feature vector.

C. Local Texture Statistic Operators

This section presents simple texture operators, which according to our knowledge have not been described elsewhere yet. All represent joint distribution of local statistical features calculated on the image. The locality is defined by a sliding window which side is equal to 7 pixels. Application of this neighbourhood allows also assuming the rotation invariance of the achieved operators. Following operators are introduced:

1) mean histogram (MH) - for each pixel the mean value in the window is calculated and the results are presented as a histogram of 64 bins;
2) min-max histogram (MMH) - for each pixel the minimal and maximal value in the window are found and its absolute difference is the value stored in the histogram of 64 bins;
3) mean-variance histogram (MVH) - for each pixel the mean and variance in the window are calculated and the result indexes two dimensional histogram (16x16 bins).

III. Datasets

There have been exploited two data sets to evaluate the performance of all this methods. The Brodatz data set with introduced rotation of the texture and the Photometric Image Database was exploited as it not only contains images of rotated texture but also with different lighting conditions. It assures that the achieved results will correspond to those found for real data analysis.

A. Brodatz

The Brodatz data set exploited in this study is based on the database prepared in [9] and [10]. It consists of images from 16 classes photographed from Brodatz album [18]. Each class originally was represented by 7 images of 180 x 180 resolutions. The images were rotated by the angle of 0, 20, 30, 45, 60, 70, 90, 120, 135, and 150 degree. Additionally, each image was partitioned into 9 images of 60 x 60 pixels. That resulted in 700 (630 small and 70 original) images representing each class. Examples of the classes are presented in Fig. 1.

B. Photometric Image Database

The Photometric Image Database (PID) was prepared by Jerry Wu [19] in the Texture Lab, Heriot-Watt University in Scotland. It consists of 39 classes of different textures. Each class is represented by 57 images of 512 x 512 pixel resolution. The texture in each class is rotated as well as the lighting changes and rotates. For this research 16 classes have been chosen (for examples see Fig. 2 and as in case of Brodatz database each image was divided into 9 images (170 $\times$ 170) that gives 570 representatives for each class.

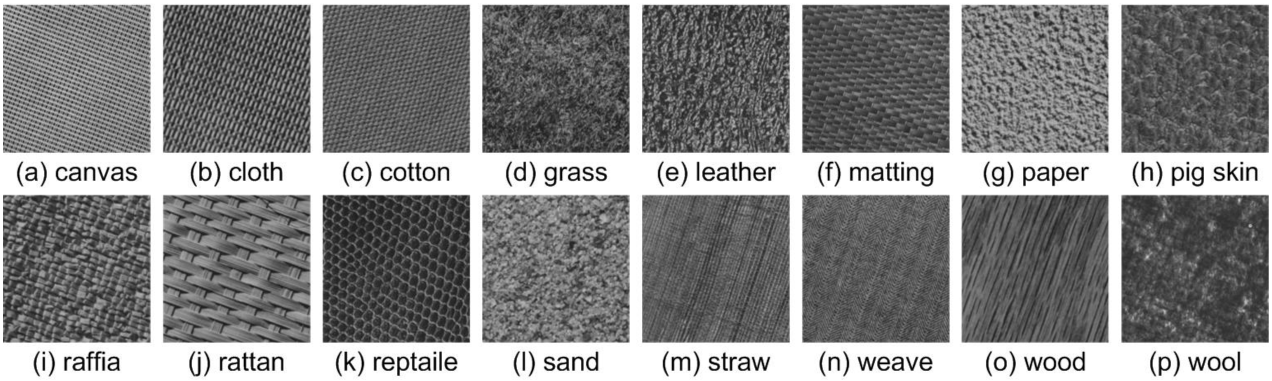

Fig. 1. Brodatz data set examples.

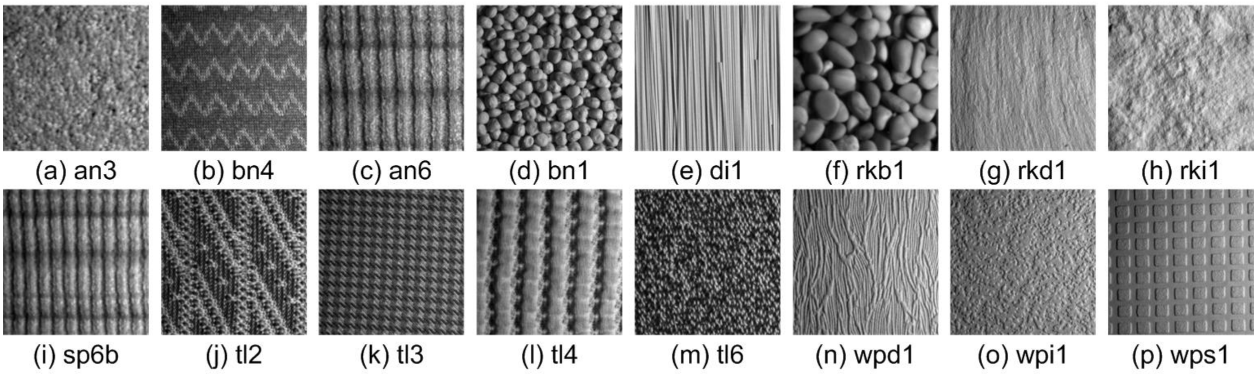

Fig. 2. Photometric image database examples.

IV. Results

In this section firstly the performance of each presented methods is given for both data sets. Then the feature vector length is diminished with application of principal component analysis (PCA) and the influence of data transformation on the classification efficiency is considered. Instead of methods names the abbreviations are used. In cases where both the features and matrices are exploited as features vectors the subscript F or M is added, respectively.

A. Methods Comparison

The aim of this experiment was to compare the efficiency of the classification of all described methods. The k nearest neighbour (kNN) classifier was applied. The number of neighbours used for classification was chosen to be 15, 25, and 35. Larger neighbourhoods were not considered. Since the training set consists of 10% of all data, what gives 70 elements for each class from Brodatz data set and 57 for PID. Therefore, using larger neighbourhood would involve bigger number of votes from neighbourring classes, what in consequence would increase the probability of erroneous classification.

Fig. 3. and 4. present graphical interpretation of achieved results. It is worth to notice that the results for all tested methods are very high. In case of Brodatz data set the weakest $GTDM_F$ method correctly classified around 93% of data. While considering the 15 object neighbourhoods there were 3 methods which classification efficiency was 100% (COM_M, MVH, NH) and next 6 which performance exceeds 99% (MMH, LBP, RLM_M, $GRTD_M$, MH, COM_F). As supposed increasing neighbourhood used for classification resulted in diminishing accuracy of correct classification ratio.

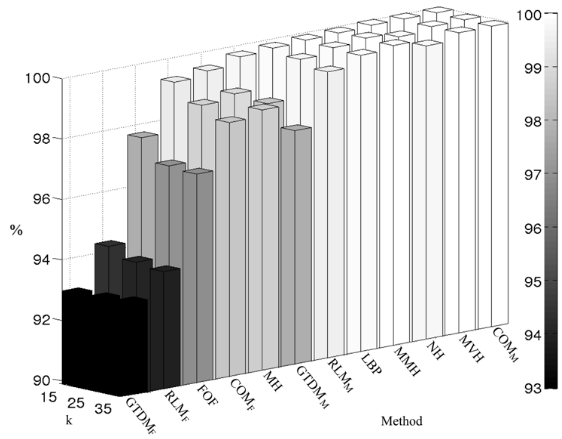

Fig. 3. Classification of brodatz data set with kNN classifier applied to all methods.

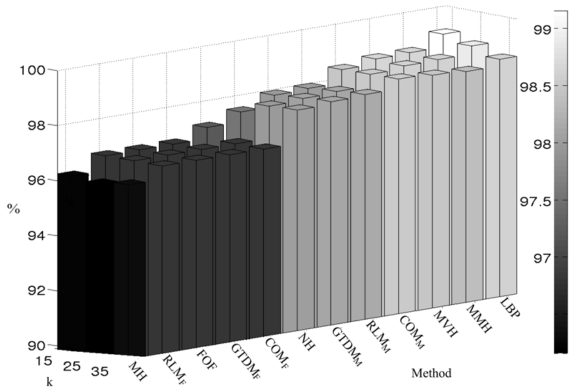

Fig. 4. Classification of PID data set with kNN classifier applied to all methods.

The performance of all classifiers on the PID data set was slightly worse, as none of the methods achieved 100% correct classification. The best efficiency here is for LBP on the level of 99.15% for neighbourhood equal to 15 elements. However, the lower efficiency of the methods on this data set results probably from the additional lighting changes which are introduced in data. Moreover, noticeable is the tendency of losing classification efficiency when the increasing neighbourhood is kept.

Additionally, it is also notable that the sophisticated techniques (e.g. LBP, COM, RLM) do not outperform the simple ones (MMH, MVH). The bigger difference is visible only in case of PID data set. It seems that, however they are prone to lighting changes, they describe the texture characteristics well.

Finally, in both cases the better performance was achieved by techniques based on the structures (e.g. COM_M) in comparison to that achieved by features derived from this data structures (e.g. COM_F). Hence, as considered the information in the structure is sufficient. Therefore, it is an effective competitor for features, which other drawback is time needed for calculation. On the other hand, the structures store probably redundant data. Moreover its high dimensionality influences also the classification time performance. In consequence, further consideration to address these problems is described in next experiment.

B. Dimension Reduction

As noticed, many of the texture feature vectors are built from very big structures. The information stored in them is redundant and the size influences the classification procedure time consumption. Therefore, PCA was applied to the feature vectors in order to extract the most descriptive part of the data.

TABLE I: FEATURE VECTOR LENGTH FOR 100, 95, AND 90 % OF INFORMATION SUSTAINED WHEN APPLYING PCA.

Information	100	95		90	
Method		PID	Brodatz	PID	Brodatz
	Len.	[%]	[%]	[%]	[%]
RLM_M	640	9.38	6.72	7.03	5.16
LBP	416	3.13	4.57	1.44	1.92
COM_M	256	3.91	5.47	2.73	3.13
MVH	256	3.13	4.69	2.34	3.52
$GTDM_M$	256	43.36	41.02	28.91	34.77
MH	64	28.13	17.19	17.19	10.94
MMH	64	17.19	34.38	6.25	26.56
NH	64	25.00	39.06	15.63	31.25
COM_F	28	3.57	7.14	3.57	7.14
RLM_F	12	16.67	8.33	16.67	8.33
FOF	6	16.67	16.67	16.67	16.67
$GTDM_F$	5	20.00	20.00	20.00	20.00

TABLE I presents the length of each feature vector, which consists of all gathered information (see 2nd column). Next columns show the percent of the original number of features exploited to describe 95 and 90 % of original information. The application of PCA allowed diminishing the feature vector length considerably for all methods. However, in case where the feature vector has already been rather short (less than 20 features) this operation may influence the classification results a lot.

Fig. 5. and 6. present the comparison of classification performance achieved by kNN classifier for the neighbourhood equal 15, which in previous case gave the best results. In this graph the comparison of performance depending of the percent of original information (100, 95, 90) is depicted.

The reduction of feature vector length in order to assure remaining 95% of information almost did not change the results. In some cases they even become better (Brodatz: MMH, LBP, $GTDM_M$, MH; PID: $GTDM_M$, MH, LBP, MMH, RLM_M, RLM_F). However, in case of Brodatz the classification was impossible for FOF, RLM_F, and $GTDM_F$ methods, while for PID for COM_F, FOF, and $GTDM_F$. Therefore, results for these methods are not presented. It is interesting, that in case of PID the improvement in performance allows to achieve 99.77% for $GTDM_M$ method. Still the performance of the simple techniques do not differ considerably when compared to that of more sophisticated methods and the structure based methods classify better than methods based on features.

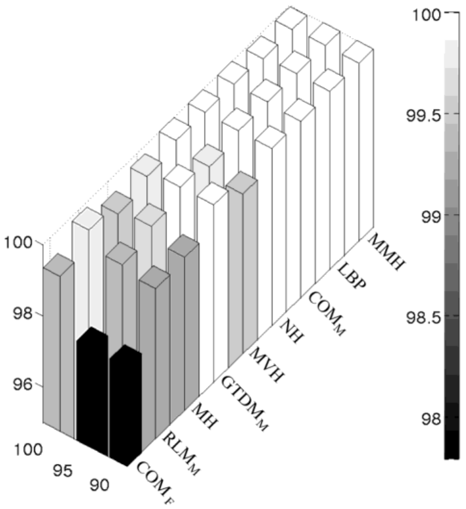

Fig. 5. Influence of feature vector length dimension on classification performance on Brodatz data set.

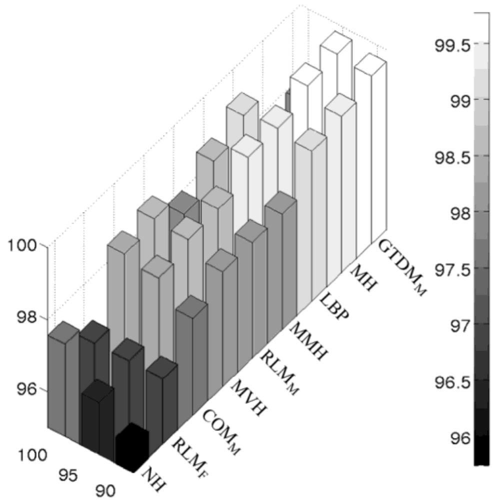

Fig. 6. Influence of feature vector length dimension on classification performance on PID data set.

V. Conclusions

This study concentrates on the problem of texture description for classification needs. The comparison of well-known textural features with simple texture descriptors is presented.

In order to assure that the results will correspond to data acquired in real world two benchmark data sets are exploited: Brodatz and PID. In Brodatz the texture rotation is introduced, whereas PID data set has already photographed the texture data with different rotation and under different lighting conditions.

Classification experiments on both data sets proved that all methods distinguish textures very well, as the correct classification results are in the range 92-100%. Although, the performance was lower in case of PID data set that suggests that there are still problems when dealing with changing lighting conditions. Moreover, the results reviled that the sophisticated methods do not outperform the simple ones. Furthermore, application of the structures as feature vectors return better results than exploiting the features derived from those structures.

It was also analyzed whether reducing feature vector length by applying PCA influences the classification results. It was proven that using 95\% of original information however diminishes the feature vector length considerably does not influence the classification performance.

References

[1] J. Malik and P. Perona, "Preattentive texture discrimination with early vision mechanisms," *J. Opt. Soc. Am. A*, vol. 7, no. 5, pp. 923-932, 1990.

[2] F. Albregtsen, B. Nielsen, and H. E. Danielsen, "Adaptive Gray Level Run Length Features from Class Distance Matrices," presented at 15th International Conference on Pattern Recognition, 2000, 3, 3746.

[3] M. Amadasun and R. King, "Textural features corresponding to textural properties," *IEEE Transactions on System, Man Cybernetics*, 1998, vol. 19, no. 5, pp. 1264-1274.

[4] C. M. Chu, C. M. Seghal, and J. F. Greenleaf, "Use of gray value distribution of run lengths for texture analysis," *Pattern Recognition Letters*, vol. 11, pp. 415-420, 1990.

[5] M. M. Galloway, "Texture analysis using gray level run lengths," *Computer Graphics and Image Processing*, 1975, vol. 4, pp. 172-179.

[6] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, 1973, SMC-3, pp. 610-621.

[7] V. Manian, R. Vasquez, and P. Katiyar, "Texture classification using logical operators," *IEEE Transactions on Image Analysis*, 2000, vol. 9(10), pp. 1693-1703.

[8] A. Materka and M. Strzelecki, "Texture Analysis Methods - A Review," Technical University of Lodz, Institute of Electronics, 1998

[9] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Gray scale and rotation invariant texture classification with local binary patterns," *Lecture Notes In Computer Science*, vol. 1842, pp. 404-420, 2000.

[10] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2002, vol. 24, no. 7, pp. 971-987.

[11] X. Tang, "Texture Information in Run-Length Matrices," *IEEE Trans. on Image Processing*, 1998, vol. 7, no. 11, pp. 1602-1609

[12] M. Tuceryan and Jain, "Texture Analysis in The Handbook of Pattern Recognition and Computer Vision(2nd Edition)," A. K. C. H. Chen, L. F. Pau, and P. S. P. Wang (ed.), World Scientific Publishing Co., 1998, pp. 207-248.

[13] S. W. Zucker and D. Trerzopoulus, "Finding Structure in Co-occurrence Matrices for Texture Analysis," *Computer Graphics and Image Processing*, vol. 12, pp. 286-308, 1980.

[14] H. Dong-Chen and L. Wang, "Texture features based on texture spectrum, " *Pattern Recognition*, vol. 24, no. 5, pp. 391-399, 1991.

[15] K. K. Holli, L. Harrison, R. Dastidar, M. Waljas, S. Liimatainen, T. Luukkaala, J. Ohman, S. Soimakallio, and H. Eskola, "Texture analysis of MR images of patients with Mild Traumatic Brain Injury," *BMC Medial Imaging*, vol. 10, no. 8, 2010.

[16] D. Vince, K. Dixon, R. M. Cothren, and J. F. Cornhill, "Comparison of texture analysis methods for the characterization of coronary plaques in intravascular ultrasound images," *Computerized Medical Imaging and Graphics*, 2000, vol. 24, pp. 221-229

[17] M. Lettner, P. Kammerer, and R. Sablatnig, "Texture Analysis of Painted Strokes," in W. Burger and J. Scharinger (Eds.), 28th Workshop of the Austrian Association for Pattern Recognition, pp. 269-276, Hagenberg, Austria, June 2004.

[18] P. Brodatz, *Textures: A photographic album for artists and designers*, Dover, 1966.

[19] J. Wu. Photometric image database. [Online]. Available: http://www.macs.hw.ac.uk/texturelab/resources/databases/jwdb/index.htm.

Karolina Nurzyńska received her M.E. and Ph.D. degree in the field of computer science from the Silesian University of Technology, Poland in 2005 and in 2009, respectively. She was a researcher in the School of Electrical and Computer Engineering, Kanazawa University. Her research interests include image processing and 3D surface reconstruction.

Mamoru Kubo received B.E. and M.E. degrees from Nagoya Institute of Technology, Japan in 1990 and 1992, respectively. He is an assistant professor in the School of Electrical and Computer Engineering at Kanazawa University, Japan. His research interests include photogrammetry and remote sensing. He is a member of IEEE.

Ken-ichoro Muramoto received B.E. and M.E. degrees from Toyama University, Japan in 1971 and 1973, respectively. He received the Ph.D. degree in Engineering from Kyoto University, Japan in the field of image information science. He has also received the doctor of medical science degree from Toyama Medical and Pharmaceutical University in the field of neurophysiology. He was a professor in the Faculty of Electrical and Computer Engineering, Institute of Science and Engineering at Kanazawa University, Japan. He is currently the president in the Ishikawa National College of Technology, Japan. His research interests include image processing, pattern recognition, human vision and remote sensing. He is a member of IEEE.