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Local Oriented Statistics Information Booster (LOSIB) for texture classification

Oscar García-Olalla
School of Electrical and Computer Engineering
University of León
León, Spain
ogaro@unileon.es

Enrique Alegre
School of Electrical and Computer Engineering
University of León
León, Spain
enrique.alegre@unileon.es

Laura Fernández-Robles
School of Electrical and Computer Engineering
University of León
León, Spain
lferr@unileon.es

Víctor González-Castro
École Nationale Supérieure des Mines de Saint-Étienne
Laboratoire LGF UMR CNRS 5307
42023 Saint-Etienne Cedex 2, FRANCE
victor.gonzalez@emse.fr

***Abstract*—Local oriented statistical information booster (LOSIB) is a descriptor enhancer based on the extraction of the gray level differences along several orientations. Specifically, the mean of the differences along particular orientations is considered. In this paper we have carried out some experiments using several classical texture descriptors to show that classification results are better when they are combined with LOSIB, than without it. Both parametric and non-parametric classifiers, Support Vector Machine and k-Nearest Neighbourhoods respectively, were applied to assess this new method. Furthermore, two different texture dataset were evaluated: KTH-Tips-2a and Brodatz32 to prove the robustness of LOSIB. Global descriptors such as WCF4 (Wavelet Co-occurrence Features), that extracts Haralick features from the Wavelet Transform, have been combined with LOSIB obtaining an improvement of 16.94% on KTH and 7.55% on Brodatz when classifying with SVM. Moreover, LOSIB was used together with state-of-the-art local descriptors such as LBP (Local Binary Pattern) and several of its recent variants. Combined with CLBP (Complete LBP), the LOSIB booster results were improved in 5.80% on KTH-Tips 2a and 7.09% on the Brodatz dataset. For all the tested descriptors, we have observed that a higher performance has been achieved, with the two classifiers on both datasets, when using some LOSIB settings.**

***Keywords*—texture retrieval, booster, descriptor**

I. INTRODUCTION

Texture analysis is a challenging open problem in computer vision. It refers to a set of processes applied to detect and describe spatial variations of the gray level of all the pixels in an image. Nowadays, there are multiple fields that profit from automatic texture retrieval, as it makes processes faster with no need of many qualified staff. For example, Wang et al developed a texture retrieval method of Thyroid Gland SPECT images based on the gray level co-occurence matrix [1]. Likewise, Zhou and his group [2] used gray level co-occurrence features for breast cancer recognition, obtaining a precision of 69% using the Tamaura dataset. In the biological field, Alegre et al proposed a texture and moment-based classification of the boar sperm acrosome integrity obtaining very interesting results [3]. In [4], González-Castro et al proposed an adaptive method with no need of training for texture classification based on the pattern spectrum descriptor. Haralick features, Wavelet transform and Local descriptors are very well known techniques with high performance in texture retrieval processes.

Haralick features have been widely used in the last 30 years for texture description. Recently, Chaddad et al [5] developed a system founded on Haralick features to detect colon cancer cells. Similarly, a local Haralick features extraction method was used by Ribaric and Lopar in a palmprint recognition application obtaining very promising results [6].

Besides, methods based on the Wavelet transform have been developed in the last years showing very high performances on texture retrieval problems. In [7], Carbunaru et al proposed a system for textile image retrieval using independent component analysis (ICA) applied to the wavelet transform responses achieving average precision rates of 89%-94%. Rakvongthai et al evaluated the performance of Wavelet transform with very noisy images demonstrating the good efficiency of the transform on these environments [8].

Lastly, local descriptors have become more and more important in the last few years. Concretely, the Local Binary Pattern (LBP) descriptor proposed by Ojala et al [9] have been widely used due to their simplicity and high capability to extract the intrinsic features from the textures. García-Olalla et al [10] proposed an adaptive LBP method for vitality assessment of boar sperm. Guo and his group have been developing several modifications of LBP such as LBP variance (LBPV) [11], complete LBP (CLBP) [12] or adaptive LBP (ALBP) [13].

Too many datasets have been created in order to assess texture descriptors. One of the most challenging one is the KTH-TIPS 2a [14]. In [15], [16], García-Olalla et al proposed an adaptive local binary pattern and evaluated it along with several modifications of LBP, consolidating their method as the best one. Other works that use KTH-TIPS 2a are the one developed by Chen et al[17], which proposes a robust method for image description called WLD, or the work carried out by Sharma et al [18] which has developed a descriptor based on local high order statistics. Another widely used dataset is the Brodatz32 dataset [19], which contains gray scale images of 32 textures under rotation and scale attacks, presenting an open problem. We have tested our proposal with these two dataset since we consider that they are quite representative for texture problems.

The rest of the paper is organised as follows. In section II the methodology of this work is described. The experiments and datasets are shown in section III and finally, in section IV

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the conclusions are discussed.

II. METHODOLOGY

Nowadays, more and more methods for images description are being developed. In face recognition, algorithms based on local features as LBP or statistical analysis as PCA, are commonly used. In object retrieval, methods depend on keypoint detectors such as SURF or SIFT are taking all the centre stage. Other methods relying on transforms such as Wavelet or Fourier are very used in image description.

A. Local oriented statistical information booster (LOSIB)

The main purpose of the Local Oriented Statistical Information Booster (LOSIB) is to enhance the performance of a texture descriptor.

The basic concept is to add local oriented statistical information computed along all pixels of the image. This information is rarely taken into account when texture is described and gives extremely useful information for texture discrimination. In this work, the combination of LOSIB with widely used texture descriptors was done by concatenation of both vectors.

One important factor in LOSIB extraction is the depth of the neighbourhood used to compute the statistical moments, as the information retained by LOSIB at each pixel is less local. Depending on the image dataset, very local or more loose global information can achieve best performance.

Another factor is the number of neighbours in the neighbourhood. In this sense, more neighbours means that a higher number of different orientations have been taken into account. As the texture becomes more heterogeneous, the number of neighbours should be increased in order to capture all the variety of the image. However, using excessive orientations on homogeneous textures may be counter-productive due to the loss of weight of the important ones. Therefore, the nomenclature for this method is LOSIB(R,P) where R is the radius of the neighbourhood and P the number of neighbours.

Let c be a pixel at position (x_c, y_c) of the image, p be a pixel of its neighbourhood (with $p \in \{0, 1, ..., (P-1)\}$), whose coordinates are (x_p, y_p), and let g_c and g_p be their respective grey level values. In order to obtain the LOSIB of an image, it is first necessary to extract the absolute differences d_p between the grey level values g_c and g_p, for all pixels c of the image, as shown in equation (1). Figure 1 depicts an example of this oriented difference extraction at three pixels.

$$d_p(x_c, y_c) = |g_c - g_p| \quad (1)$$

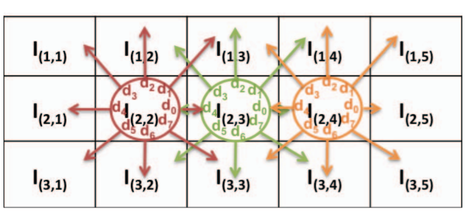

Fig. 1. Extraction of the absolute difference of gray-level values for three pixels to compute LOSIB(1,8).

Given a pixel c, the coordinates (x_p, y_p) of its p-th neighbour are obtained by means of equation (2).

$$(x_p, y_p) = (x_c + R\cos(2\pi p/P),\ y_c + R\sin(2\pi p/P)) \quad (2)$$

The values of the neighbours that are not in the centre of grids can be estimated by interpolation of their connected pixels.

Then, the mean of all the differences along the same orientation is computed following equation (3), where N and M are the number of rows and columns of the image, respectively.

$$\mu_p = \frac{\sum_{x_c=1}^{M} \sum_{y_c=1}^{N} d_p(x_c, y_c)}{M \cdot N} \quad (3)$$

In figure 2 the histogram of all the absolute differences along the orientation $p = 0$ and the value μ_0 for an image of KTH-TIPS 2a dataset is shown.

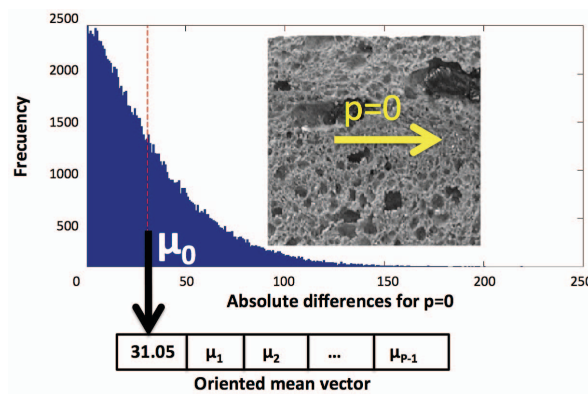

Fig. 2. Example of a histogram of all the absolutes differences along the orientation 0° (thus, $p = 0$) and the mean value used to yield the final LOSIB.

Thereby, LOSIB will have as many features as neighbours are in the considered neighbourhood and it represents the mean difference for all the orientations shown in equation (4).

$$\text{LOSIB}(R, P) = \bigcup_{p=0}^{P-1} \mu_p \quad (4)$$

An example of the orientations of a LOSIB(1,8) is shown in figure 3 for clarification.

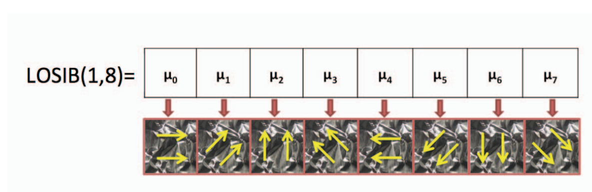

Fig. 3. Different orientations using 8 neighbours.

B. Global descriptors

In the last years, many global texture descriptors have been developed in texture retrieval problems. In this work we have assessed the performance of LOSIB when combined with some classic moments such as Hu [20], Legendre [21], Zernike [22] or Flusser [23].

In addition, other descriptors based on the Haralick features [24] computed from the co-occurrence matrix have been assessed. These descriptors are Wavelet co-occurrence features and Wavelet statistical features. We address the reader interested in further details about them to [3].

C. Local descriptors

Several local descriptors found on the Local Binary Pattern [9] have been assessed. The main idea of LBP is to describe the texture of grayscale images extracting their local spatial structure. For each pixel, a pattern code is computed by comparing its value with the value of its neighbours:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \ , \ s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (5)$$

where g_c is the value of the central pixel, g_p is the value of its neighbour p, P are the number of neighbours and R is the radius of the neighbourhood. Afterwards, the whole image is characterised by means of a histogram of its LBPs.

Furthermore, LOSIB has been assessed in combination with some variants of LBP, such as adaptive LBP (ALBP) [13], LBP variance (LBPV) [11] and Complete LBP (CLBP) [**?**]

D. LOSIB normalization

In order to adjust the weight of both the texture descriptor and the LOSIB vector, a weighted concatenation has been performed (see equation (6)).

$$X_{final} = [w_1 \cdot X, \ w_2 \cdot \text{LOSIB}] \quad (6)$$

where X is the classical descriptor, w_1 and w_2 are the weighted factors of the classical descriptor and the LOSIB, respectively, and X_{final} is the final (i.e. enhanced) descriptor. Several tests have been carried out to determine the optimal configuration obtaining the best results with weights $w_1 = 1$ and $w_2 = \Delta$ where Δ is obtained using the equation (7).

$$\Delta = 10^{\nu_D - \nu_L} \quad (7)$$

where ν_D and ν_L are the highest orders of magnitude in the classical descriptor and in LOSIB, respectively.

III. Experiments

A. Texture datasets

1) KTH-TIPS 2a dataset: KTH-TIPS 2a dataset is composed by 4752 images for material categorization [14]. It contains 11 materials (lettuce, brown bread, white bread, aluminium, corduroy, cork, cotton, cracker, linen, wood and wool) with 108 images for four different samples from each material resulting in 432 images per class. All samples were taken at 3 poses, 4 different illumination conditions and 9 scales. All this variations make a very challenging dataset. In figure 4 some examples of textures under different conditions are shown.

Fig. 4. Examples of some images of the KTH-tips 2a dataset under different scales and illumination. From top to bottom: Brown bread, cotton, wool and lettuce leaves.

2) Brodatz32 dataset: Brodatz32 [19] is a subset of 32 images (each image forms a class) of the original Brodatz dataset. It is composed of 2048 sub images (64 images per class) which comprise the following subsets with all the images of 64×64 pixels: 16 "original" images, 16 rotated versions of the "original" images, 16 scaled versions of the "original" images and 16 rotated and scaled versions of the "original" images. As a preprocessing step, all the images in the dataset have uniform gray level histogram. In figure 5 we can see examples of each of the 32 "original" images.

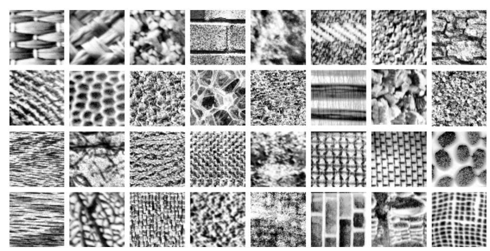

Fig. 5. Brodatz dataset examples of each class.

B. Experimental setup

1) KTH-TIPS 2a dataset: The experimental setup used for the KTH-TIPS 2a dataset is the standard protocol developed by Caputo et al and used in several works [14], [17]. It consists of taking one of the samples of each material for test and the rest for training, which conforms a more challenging setup than dividing the images randomly between training and test. In this work, we carried out four classifications using this method to increase its robustness, one classification using each texture sample as the test set. The mean of the hit rate in each iteration was computed. We have used a Support Vector Machine (SVM) with the one-vs-one paradigm to classify the images. We have selected the Least Squares training algorithm and a polynomial kernel of order 2. We have also classified with a non parametric k-Nearest Neighbour (kNN) algorithm.

2) Brodatz32 dataset: The setup of the Brodatz32 experiments is quite similar to the KTH-TIPS 2a one. However, Brodatz32 does not have different samples in each class so we have used a 4-fold cross validation in order to avoid randomness, extracting the average as the final accuracy result. In this way, we have used a 75% of images as training set and the remaining 25% as the test set. A SVM trained with

Least Squares and a polynomial kernel with order 2 to find the decision boundary has been used. Since the dataset is multiclass, a one-vs-one paradigm has been used.

C. KTH-TIPS 2a dataset results

The first experiment deals with the classification of KTH-TIPS 2a using a one-vs-one SVM paradigm and it demonstrates that the LOSIB enhancer improves the hit rate over all the classical descriptors. Three configurations of LOSIB have been evaluated: LOSIB(1,8), LOSIB(2,16), and a concatenation of both (which will be called LOSIB(1,8)+LOSIB(2,16)). Figure 6 depicts the results using the classical global descriptors. It is specially remarkable the cases of the Hu, Legendre, Flusser and Zernike moments. They yield a poor performance by themselves alone, but LOSIB makes their accuracy to increase more than a 50% in all cases (161% in the case of the Hu moments) The best hit rate is 63.33%, obtained by Haralick and LOSIB(1,8)+LOSIB(2,16). The improvement of the most

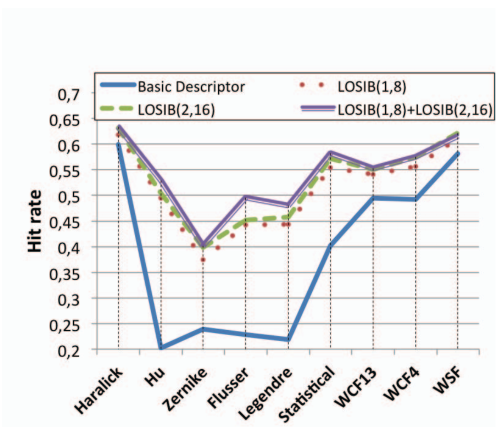

Fig. 6. Results on the KTH-TIPS 2a dataset using the global descriptors and the combination with the LOSIB(1,8), the LOSIB(2,16) and both of them.

recently used global descriptors is clearer shown in figure 7. Methods based on the Haralick features, computed from the co-occurrence matrix of the texture directly (called Haralick), or from the Wavelet response (called WCF4 and WCF13 [3]) obtain better results with the LOSIB(1,8)+LOSIB(1,16), outperforming the descriptor in a 16.81% with WCF4. However, using the Wavelet Statistical Features (WSF) the best improvement was obtained with just the LOSIB(2,16) (6,91%). The amelioration of LOSIB with local descriptors of the LBP family on KTH-TIPS 2a are slightly lower than the ones obtained with the global descriptors but they achieved better performance than by themselves alone.

In figure 8 the hit rate obtained in all the tests carried out is shown. The best hit rate was 71.44%, achieved with CLBP and LOSIB(1,8) but the higher improvement was obtained with LOSIB(1,8) and LBPV. LBP descriptor achieved lower hit rates when it is combined with LOSIB(1,8) (65.11%) and LOSIB(2,16) (65.17%), rather than by itself alone (65.53%), but obtains better results with the concatenation of both of them (66.83%).

In figure 9 we can clearly see the improvement of LOSIB in relation to the LBP descriptors. As we said before, the

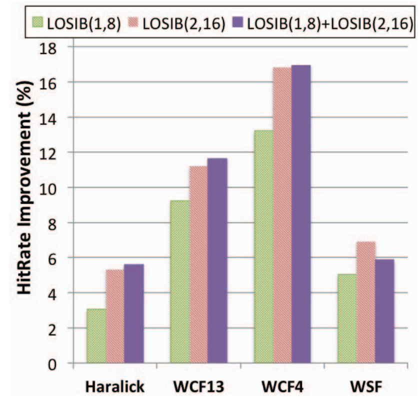

Fig. 7. Improvement of the most used global descriptors in the last years.

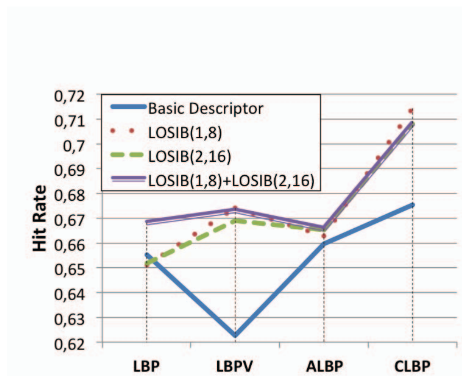

Fig. 8. Results on the KTH-TIPS 2a dataset using the LBP descriptors and the LOSIB(1,8), LOSIB(2,16) and LOSIB(1,8)+LOSIB(2,16).

LBP descriptors are just outpeformed by the combination of LOSIB(1,8)+LOSIB(2,16), but the hit rate of all the others is increased on the three experiments. The higher improvement reaches a 8.28% with LOSIB(1,8) and LBPV.

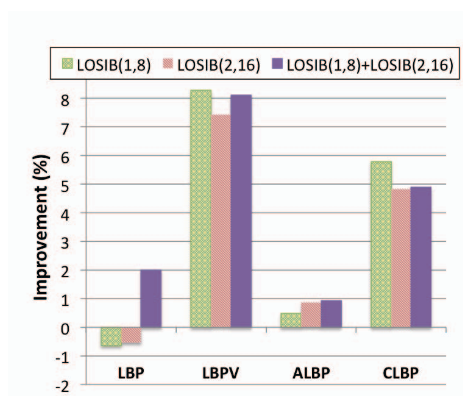

Fig. 9. Improvement of LOSIB with the LBP local descriptors.

In table I the numerical results are shown.

The good performance of our LOSIB enhancer is confirmed by the classifications carried out by the k-NN classifier. Once again, the hit rate of all descriptors is increased when they are combined with the three boosters assessed (LOSIB(1,8), LOSIB(2,16) and LOSIB(1,8)+LOSIB(2,16). In figure 10 we can see the results obtained with k-nearest neighbours using the Chi Square distance metric. The best improvement was achieved with the global descriptors while the best result was obtained using ALBP with a hit rate 62.10% when combining it with LOSIB(1,8)+LOSIB(2,16).

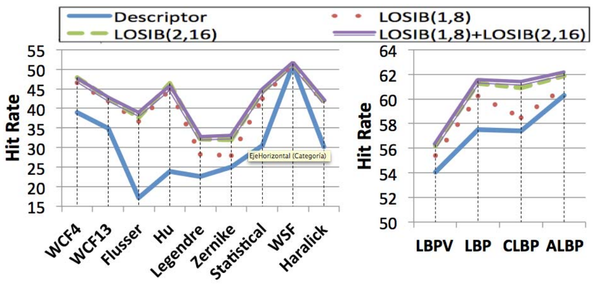

Fig. 10. Results using kNN on the KTH-TIPS 2a dataset. In the left, the global descriptors combined with LOSIB and in the right the local LBP family.

D. Brodatz32 dataset results

In order to assess the robustness of the LOSIB, more tests have been carried out using Brodatz32. In that case, one-vs-one SVM have been used with a 4-fold strategy. The results are shown in figure 11. In all the cases, the LOSIB booster enhance the results of the descriptors, being the best hit rate 91.06%, with LBPV and both LOSIB vectors. The higher difference was obtained again in the Haralick descriptor with an improvement of 52.29% using LOSIB(1,8)+LOSIB(2,16).In table II the numerical results are summarised.

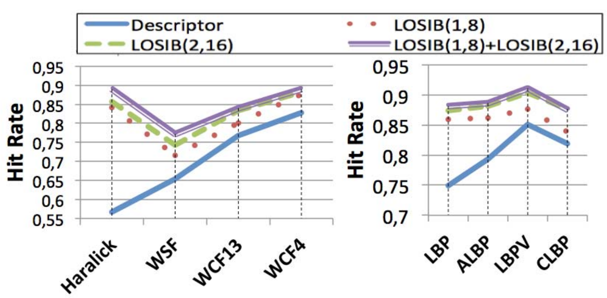

Fig. 11. Results using SVM on the Brodatz32 dataset. In the left, the global descriptors combined with LOSIB and in the right, the local LBP family with and whitout LOSIB.

IV. Conclusions

A new texture booster has been developed in order to enhance global and local descriptors (e.g. Wavelet-based feature vectors and Local Binary Pattern, respectively). Local Oriented Statistical Information Booster (LOSIB) extracts the local oriented information of the image, taking into account the means of the gray value differences of the pixels and their neighbours along different orientations. Two different parameters: radius of the neighbourhood and number of neighbours, give LOSIB more reliability and robustness adapting the method to different kinds of images and problems. Several classical methods have been evaluated by themselves alone and also concatenated with LOSIB with three different parameter combinations: the first one, using eight neighbours with a depth of one pixel; the second one using sixteen neighbours with a depth of two pixels and the third one combining both of them. Results have shown that combining the descriptors with LOSIB increases the performance of the classification. Two datasets have been used, KTH-TIPS 2a and Brodatz32, obtaining better results in all the cases except when combining LBP with LOSIB(1,8) and LOSIB(2,16) separately, but outperforming always the hit rate when both of them were concatenated together. Two different classification methods have been tested in order to give more credibility to the results. A one-vs-one SVM approach with a polynomic kernel of order two and a weighted k-nearest neighbour variant. The best results were achieved with the Complete Local Binary Pattern method combined with LOSIB(1,8) obtaining a 71.44% of hit rate in KTH-TIPS 2a and using LBPV and LOSIB(1,8)+LOSIB(2,16) on Brodatz32 with a 91.06% of hit rate. While the best performance was achieved using local descriptors, the best improvement was obtained when LOSIB was combined with global descriptors, as they complement each other mixing local and global information. In conclusion, a new local texture booster has been developed which combined with all the studied descriptors outperforms the classification in all cases resulting in a very promising method.

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TABLE I. PERFORMANCE OF THE LOSIBS COMBINATIONS WITH THE GLOBAL AND LOCAL DESCRIPTORS ON THE KTH-TIPS 2A DATASET CLASSIFYING WITH SVM IN %.

Descriptor	Haralick	Hu	Zernike	Flusser	Legendre	Statistical	WCF13
Alone	59.95±2.57	20.22±2.97	23.88±1.54	22.87±5.91	21.86±4.76	40.13±5.06	49.56±4.23
LOSIB(1,8)	61.78±5.51	49.49±5.67	37.42±4.19	44.19±5.37	44.30±7.03	55.37±6.98	54.08±3.76
LOSIB(2,16)	63.15±4.37	50.40±4.97	39.84±3.34	45.16±4.36	45.79±6.05	57.15±6.18	55.07±4.10
LOSIB(1,8)+LOSIB(2,16)	**63.32**±2.96	**52.90**±4.16	**40.13**±4.13	**49.60**±4.14	**48.02**±6.75	**58.22**±3.31	**55.28**±3.37

Descriptor	WCF4	WSF	LBP	ALBP	CLBP	LBPV
Alone	49.18%±4.39	58.14±2.98	65.53±3.61	65.97±5.63	67.53±3.17	62.27±5.81
LOSIB(1,8)	55.68%±6.66	61.07±4.31	65.11±7.98	66.29±7.98	**71.44**±5.16	**67.42**±8.21
LOSIB(2,16)	57.45%±6.62	**62.16**±4.79	65.17±8.32	66.54±8.24	70.79±5.50	66.90±8.38
LOSIB(1,8)+LOSIB(2,16)	**57.51**%±5.74	61.55±4.25	**66.84**±8.00	**66.58**±8.56	70.83±5.59	67.32±6.73

TABLE II. PERFORMANCE OF THE LOSIBS COMBINATIONS WITH THE GLOBAL AND LOCAL DESCRIPTORS ON THE BRODATZ32 DATASET CLASSIFYING WITH SVM IN %.

Descriptor	Haralick	WSF	WCF13	WCF4	LBP	ALBP	LBPV	CLBP
Alone	56.59±5.45	65.47±3.66	76.76±2.80	82.81±1.77	74.90±2.51	79.39±3.48	85.10±3.25	81.88±2.23
LOSIB(1,8)	84.13±1.42	71.58±3.21	80.03±3.15	87.70±2.29	85.89±3.87	86.18±3.43	87.65±3.19	83.84±2.11
LOSIB(2,16)	85.64±2.08	74.27±3.03	83.44±2.85	88.28±3.38	87.35±2.43	88.18±3.51	90.28±3.13	**87.70**±1.66
LOSIB(1,8)+LOSIB(2,16)	**89.01**±2.20	**77.15**±3.21	**83.94**±2.45	**89.06**±3.00	**88.18**±2.58	**88.57**±2.29	**91.06**±4.04	87.55±2.03

REFERENCES

[1] X. Wang, J. He, and Z. Lv, "Texture-based retrieval of thyroid gland spect image," in *Biomedical Engineering and Informatics, 2009. BMEI '09. 2nd International Conference on*, 2009, pp. 1–5.

[2] J. Zhou, C. Feng, X. Liu, and J. Tang, "A texture features based medical image retrieval system for breast cancer," in *Computing and Convergence Technology (ICCCT), 2012 7th International Conference on*, 2012, pp. 1010–1015.

[3] E. Alegre, V. González-Castro, R. Aláiz-Rodríguez, and M. T. García-Ordás, "Texture and moments-based classification of the acrosome integrity of boar spermatozoa images," *Computer Methods and Programs in Biomedicine*, 2012.

[4] V. Gonzalez-Castro, E. Alegre, O. Garcia-Olalla, L. Fernandez-Robles, and M. T. Garcia-Ordas, "Adaptive pattern spectrum image description using euclidean and geodesic distance without training for texture classification," *IET Computer Vision*, 2012.

[5] A. Chaddad, C. Tanougast, A. Dandache, and A. Bouridane, "Extraction of haralick features from segmented texture multispectral bio-images for detection of colon cancer cells," in *Informatics and Computational Intelligence (ICI), 2011 First International Conference on*, 2011, pp. 55–59.

[6] S. Ribaric and M. Lopar, "Palmprint recognition based on local haralick features," in *Electrotechnical Conference (MELECON), 2012 16th IEEE Mediterranean*, 2012, pp. 657–660.

[7] A.-E. Carbunaru, D. Coltuc, M. Jourlin, and L. Frangu, "A texture descriptor for textile image retrieval," in *Signals, Circuits and Systems, 2009. ISSCS 2009. International Symposium on*, 2009, pp. 1–4.

[8] Y. Rakvongthai and S. Oraintara, "Statistical texture retrieval in noise using complex wavelets," *Signal Processing: Image Communication*, vol. 28, no. 10, pp. 1494 – 1505, 2013.

[9] T. Ojala, M. Pietikainen, and D. Harwood, "Performance evaluation of texture measures with classification based on kullback discrimination of distributions," in *Proceedings of the 12th IAPR International Conference on Pattern Recognition (ICPR 1994)*, 1994.

[10] O. Garcia-Olalla, E. Alegre, L. Fernandez-Robles, and M. T. Garcia-Ordas, "Vitality assessment of boar sperm using an adaptive lbp based on oriented deviation," in *Asian conference in computer vision. Local binary Pattern Workshop*, 2012.

[11] Z. Guo, L. Zhang, and D. Zhang, "Rotation invariant texture classification using lbp variance (lbpv) with global matching," *Pattern Recognition*, vol. 43, no. 3, pp. 706–719, 2010.

[12] Z. Guo, L. Zhang, and D. Zhang, "A completed modeling of local binary pattern operator for texture classification," *Image Processing, IEEE Transactions on*, vol. 19, no. 6, pp. 1657–1663, 2010.

[13] Z. Guo, L. Zhang, D. Zhang, and S. Zhang, "Rotation invariant texture classification using adaptive lbp with directional statistical features," in *Image Processing (ICIP), 2010 17th IEEE International Conference on*, sept. 2010, pp. 285 –288.

[14] B. Caputo, E. Hayman, and P. Mallikarjuna, "Class-specific material categorisation," in *ICCV*, 2005.

[15] O. García-Olalla, E. Alegre, L. Fernández-Robles, M. T. García-Ordás, and D. García-Ordás, "Adaptive local binary pattern with oriented standard deviation (albps) for texture classification," *EURASIP Journal on Image and Video Processing*, vol. 2013, no. 1, p. 31, 2013.

[16] O. Garcia-Olalla, E. Alegre, M. T. Garcia-Ordas, and L. Fernandez-Robles, "Evaluation of lbp variants using several mmetric and knn," in *LNCS Similarity Search and Applications (SISAP)*, 2013.

[17] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen, and W. Gao, "Wld: A robust local image descriptor," in *PAMI*, 2010.

[18] G. Sharma, S. Ul Hussain, and F. Jurie, "Local higher-order statistics (lhs) for texture categorization and facial analysis," in *ECCV - European Conference on Computer Vision*, Florence, Italie, Aug. 2012.

[19] K. Valkealahti and E. Oja, "Reduced multidimensional co-occurrence histograms in texture classification," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 20, no. 1, pp. 90–94, 1998.

[20] M.-K. Hu, "Visual pattern recognition by moment invariants," *IRE Transactions on Information Theory*, vol. 8, no. 2, pp. 179–187, February 1962.

[21] M. R. Teague, "Image analysis via the general theory of moments∗," *J. Opt. Soc. Am.*, vol. 70, no. 8, pp. 920–930, Aug 1980.

[22] F. Zernike, "Diffraction theory of the cut procedure and its improved form, the phase contrast method," in *Physica*, 1934, pp. 689 –704.

[23] J. Flusser and T. Suk, "Affine moment invariants: a new tool for character recognition," *Pattern Recognition Letters*, vol. 15, no. 4, pp. 433 – 436, 1994.

[24] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 3, no. 6, pp. 610–621, November 1973.