Comparison between 2D and 3D Local Binary Pattern Methods for Characterisation of Three-Dimensional Textures

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Abstract. Our purpose is to extend the Local Binary Pattern method to three dimensions and compare it with the two-dimensional model for three-dimensional texture analysis. To compare these two methods, we made classification experiments using three databases of three-dimensional texture images having different properties. The first database is a set of three-dimensional images without any distorsion or transformation, the second contains additional gaussian noise. The last one contains similar textures as the first one but with random rotations according x, y and z axis. For each of these databases, the three-dimensional Local Binary Pattern method outperforms the two-dimensional approach which has more difficulties to provide correct classifications.

Key words: Solid texture, Local Binary Pattern Method, Classification experiments.

1 Introduction

Texture analysis is an important and old topic of image analysis and computer vision. Research in this domain can be divided in three types of problems including texture classification, texture segmentation and texture synthesis (which is often used in image compression). This paper deals with the first problematic and presents methods for characterization of three-dimensional textures. Existing feature extraction techniques can be divided into four categories [1] that is to say statistical, geometrical, frequential and model based methods. All these methods have been mainly developed and experimented on two-dimensional texture images. Recently, some of these methods have been extended to three dimensions most often in order to analyse three-dimensional medical images.

The statistical methods are based on a quantitative evaluation of gray level distribution in the images. Then, a texture is described by a collection of statistical parameters which represent the statistical properties of pixel intensities and their spatial orientation. Among these methods, there is the gray level cooccurence matrix [2, 3]. Moreover we can find Texture Spectrum method proposed by Li Wang in [4] which divides an image into a set of essential small units called texture units. This method has been a source of inspiration for Local Binary Pattern [5] also used in our works.

Geometrical methods analyse the structure of texture by identifying basis elements called "texton". A well known method is the Voronoi Tesselations used by Turceryan and Jain in [6] to analyse textures. Each cell of a Voronoi Tesselation is used to create a primitive and the gathering of similar cells defines a texture.
Model based methods needs to construct a model to synthesize and describe textures. Estimating the parameters of these models allows to characterize image features. Markov random fields [7] and fractal models [8] are two exemples of these methods.
For texture discrimination, frequential methods try to catch up with human vision. These methods regroup the popular Fourier Transform but also Gabor filters, used for the first time in image analysis by Turner [9], and wavelet transform. In [10], Mallat first suggested the use of pyramid-structured wavelet transform for texture analysis. Extension of this method was proposed with wavelet packets [11] or wavelet frames [12].
Our purpose is to develop and evaluate an extension of Local Binary Pattern method to three dimensions for three-dimensional texture analysis. We choose to work with this method because of its good results in two dimensions [13].
Section 2 presents a brief state of the art of existing texture characterisation methods used on three-dimensional textured images. Section 3 describes the Local Binary Pattern method and section 4 our proposition for an extension to three-dimensional domain. Finally, we present classification results using different parameters to evaluate our adaptation and to compare two-dimensional and three-dimensional Local Binary Pattern features.

2 Related works

Various kinds of research have been conducted to analyse two-dimensional texture. However, a little bit of these methods have been investigated to analyse solid texture. In [14], Suzuki *et al* propose to extend higher order local autocorrelation method (HLAC) to three dimensions. Three-dimensional data is handled using a three-dimensional HLAC mask which is a solid cube divided into a $3 \times 3 \times 3$ grid. With this method, texture is analysed locally. Indeed, with larger grid (for example $5 \times 5 \times 5$ or $7 \times 7 \times 7$), the number of HLAC mask patterns increases greatly and analyse a texture with a distance upper than 1 becomes difficult.
Textures have been used in many application domains like automated inspection, medical image analysis, document processing etc. In medical image analysis, there are an increasing number of three-dimensional images with Computed tomography, magnetic resonance imaging, digital radiography, positron emission tomography etc. To interpret the semantic of this three-dimensional data, texture analysis is often used and allows segmention or supervision of pathologies and their evolution.
In [15] Kovalev *et al* propose two approaches to characterize three-dimensional textures. The first method uses a three-dimensional orientation histogram computed by counting gradient vectors in various orientation bins. The second is a three-dimensional extension of Chetverikov's method of cooccurrence matrix. They apply these two models with synthetic data having different level of noise but also with medical images to quantify and monitor the progress of pathologies. These two methods characterize precisely the anisotropy of texture but for a classification problem, these features should be

associated with other texture descriptors. In [16] Ghoneim *et al* take an interest in brain tumor classification. For that, they compute two-dimensional and three-dimensional Haralick features and compare them. In all the cases, three-dimensional Haralick texture features improve tumor characterization in comparison with two-dimensional method. This paper shows the usefulness of the third dimension. Indeed, with a three-dimensional method, there is a better information about the gray level distribution and about the neighbourhood between voxels. Likewise, in [17] Showalter *et al* use three-dimensional Haralick texture features to predict micro-architectural properties of bones. For classification of subcellular location patterns, Chen and Murphy propose,in [18], a combination of three-dimensional texture features with three-dimensional Haralick texture features, three-dimensional morphological and edge features. The conclusion of this paper is clear: the combination of features methods can improve results. In [19], authors want to obtain characteristics of the hippocampus from magnetic resonance images. For that, they calculate the average energy features from two-dimensional wavelet transform of each slice of hippocampus and the energy features produced by three-dimensional wavelet transform of the hippocampus volume. Their results show that two-dimensional wavelet transform provide higher separability compared with three-dimensional wavelet decomposition. In [20], Zhang and Shen present a deformable model to segment three-dimensional ultrasound images. They compute texture features using two banks of two-dimensional Gabor filters located in the two orthogonal planes. Indeed the use of a three-dimensional Gabor filter bank should have increased the number of filters and computation time. Nevertheless with two banks of two-dimensional Gabor filters, information is lost in comparison with three dimension. This is a good example of problem met to extend two dimensional methods to three dimension.

According to all these results, statistical methods are well used to characterize three-dimensional textures. Among them, Local Binary Pattern method gives good performance in two dimensions [13] that is why we decided to extend this method to the three-dimensional domain.

3 Local Binary Pattern method

Local Binary Pattern (LBP) method has been introduced by Ojala *et al* in [5] and is strongly inspired by the texture spectrum method [4]. It has been used for facial recognition and extended for dynamic texture recognition [21]. In the LBP method, a local neighborhood is thresholded according to the gray level value of the central pixel to provide a binary pattern called texture unit. A unique LBP code is then computed according to the structure of this texture unit. An other extension of this method has been proposed in [22]. The proposed operator allows the detection of P different uniform patterns regardless of rotation or contrast and its code is given by:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U(LBP_{P,R}) \leq 2 \\ P+1 & \text{otherwise} \end{cases} \tag{1}$$

where $U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|$ is an uniformity measurement which corresponds to the number of black to white transitions along circle which defines the neighbourhood. As describe in [22], superscript ^{riu2} reflects the use of rotation invariant uniform patterns. Formula (3) express that if a pattern contains more than 2 transitions, the pattern is not uniform. An uniform pattern is represented by the LBP code which count the number of pixels with value 1.

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{2}$$

g_c is the central pixel of a set of neighbours g_p. If the coordinates of g_c are $(0,0)$, then the coordinates of g_p are given by $(-R\sin(2\pi p/P), R\cos(2\pi p/P))$ where R is a radius of a circle and P is the number of members of a circular set, as shown in figure 1. The gray values of neighbors which do not fall exactly in the center of pixels are estimated by interpolation. The $LBP^{riu2}_{P,R}$ operator ouputs a code for uniform pattern and $P+1$ otherwise. The number of apparition of each code is accumulated into a histogram of $P+2$ bins. Each bin provides an estimation of probability to find the corresponding pattern in the texture.

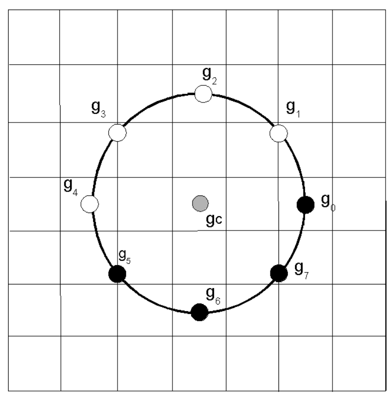


Fig. 1. Representation of a two-dimensional local binary pattern (R=2, P=8)

4 Extension of Local Binary Pattern method to three dimensions

In the litterature, we did not found a three-dimensional extension of Local Binary Pattern method. In two dimension, the classical local binary pattern method [5] allows to compute 2^8 texture units (with $R = 1$) but in three dimensions the number of texture unit increases hugely with $2^{26} = 6.7108864 \times 10^7$. That is why we decided to work using the previous idea [22] where the number of possible texture units is $P + 2$ with P the number of neighbours in the unit.

In two dimensions, we have seen that the neighbourhood of a central pixel is split up into a circular set. A logical way for the three-dimensional extension of local binary pattern method is to define neighbours in a sphere. For a central voxel g_c with the coordinates $(0,0,0)$, the coordinates of $g_{pp'}$ are given by $(R\cos(\pi p'/(S-1))\cos(2\pi p/P), R\cos(\pi p'/(S-1))\sin(2\pi p/P), R\sin(p'\pi)/(S-1))$ where R is a sphere radius, S the number of circle used to represent the sphere, and P the number of vertex in each circle (Figure 2-a). The 3D LBP texture operator can then be defined as follow :

$$LBP^{riu2}_{P',R} = \begin{cases} \sum_{p=0}^{P'-1} s(g_p - g_c) & \text{if } U(LBP_{P',R}) \leq V \\ P'+1 & \text{otherwise} \end{cases} \quad (3)$$

with $P' = (S-2) \times P + 2$,

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (4)$$

As in two-dimensional case, U is an uniformity measure function that counts the number of uniform black and white regions in the three-dimensional LBP pattern. To allow this operation, we first construct a graph using all the points on the sphere. Each vertex of the sphere is connected with its closest neighbours to obtain a related graph. Using this graph, we apply a region growing algorithm to identify regions in the three-dimensional pattern. In two dimensions, a pattern is defined as uniform when the number of regions is lower than 2. In three dimensions, we relax this condition with $V \in \{2,3\}$. Indeed, when the radius increase, proportions of uniform patterns found in an image decrease greatly (Table 1). With a radius $R = 3$ and with $V = 2$, the percentage of uniform pattern is lower than 50%. In consequence, information can be lost in quantity.

Table 1. Percentages of uniform patterns computed using databases in section 5

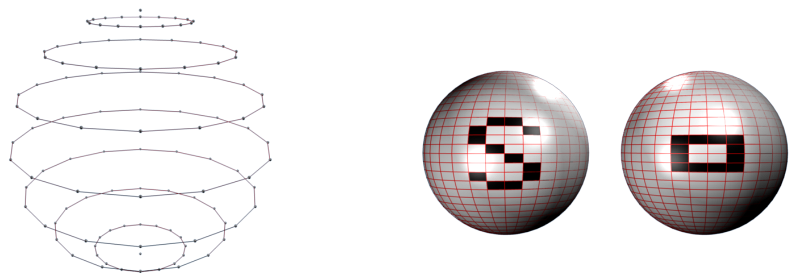
	V=2	V=3
R=1,P'=26	90.01	96.22
R=2,P'=98	59.92	80.36
R=3,P'=218	46.01	61.28

With this method, we are able to compute LBP codes in three-dimensional textured images. Nevertheless, in two dimensions, the $LBP^{riu2}_{P,R}$ code is corresponding to a unique LBP pattern but in three dimensions many LBP pattern can have the same LBP code (figure 2-b). Then, it is possible to find two different textures with the same LBP histogram. Ideally, it should compute an unique code for each uniform pattern as in two dimensions. However, the number of LBP codes would increase greatly.

5 Evaluation of our proposition

5.1 Objective and protocol

Our purpose is to test and compare two-dimensional and three-dimensional Local Binary Pattern features. To evaluate these two approaches, we decide to use a texture



(a) (b)

Fig. 2. a) Representation of a 3D local binary pattern (S=9, R=2, P=16), b) Example of two 3D Local Binary Pattern with the same LBP code ($LBP^{riu2}_{P',R} = 12$). Here, the value of black vertex is 1 and the value of the others is 0.

classification problem. For these classification experiments, a support vector machine (SVM) algorithm is used with a radial basic function (RBF) kernel $K(x, x') = exp(-\gamma \left\| x - x' \right\|^2)$ with x and x' two p-dimensional vectors and $\gamma > 0$. This kernel allows to handle the case when the relation between class labels and attributes is nonlinear. Moreover, the number of hyperparameters is low in comparison with other kernel like polynomial kernel. In our implementation, we use a free library called "LIBSVM" [23].
For classification experiments, we decide to build our own databases. The next section describes this database.

5.2 Database of three-dimensional textures

In order to test our texture extensions, we made a three-dimensional database of solid texture images. This database is now available in free access [1]. In [24], Johannes Kopf *et al* construct solid texture synthesis from two-dimensional texture images. A database is available [2] but currently there are too few images to make a classification experiment.
Our database contains three-dimensional texture images with a size of $64 \times 64 \times 64$ which has been constructed using two different methods.
With the first method, the three-dimensional textured images were constructed using two-dimensional texture images like Brodatz textures, fractal textures etc. Two or more two-dimensional texture images are interpolated to obtain a three dimensional image. Figure 3 shows an example of a three-dimensional texture image made from four two dimensional brodatz textures.

The second method consists to use geometric shapes like sphere, cube, ellipsis, etc. For exemple, to construct a gruyere texture, we place randomly white sphere with random sizes in a black three-dimensional image. Figure 4 shows two exemples of

[1] http://www.rfai.li.univ-tours.fr/fr/ressources/3Dsynthetic_images_database.html
[2] http://johanneskopf.de/publications/solid/textures/index.html

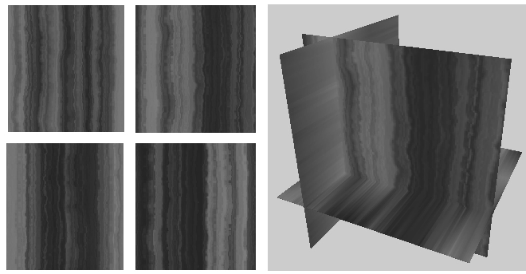


Fig. 3. Exemple of a three-dimensional textured image made with an interpolation of two-dimensional images

texture of this category. It is also possible to mix these two methods that is to say to place textured shapes randomly in a textured image of the first class. We then obtain a third category of three-dimensional images.

In [25], Van Gool *et al* describe three classes of texture with deterministic textures, stochastic textures and observable textures. The first category is characterized by the repetition of a geometrical pattern. To the contrary, stochastic textures are irregular and a pattern is not identifiable. At last observable textures can be describe by a mix between geometric and stochastic textures. Patterns are very closed but not identical. To have a complete database, we have tried to build synthetic images representative of all three classes.

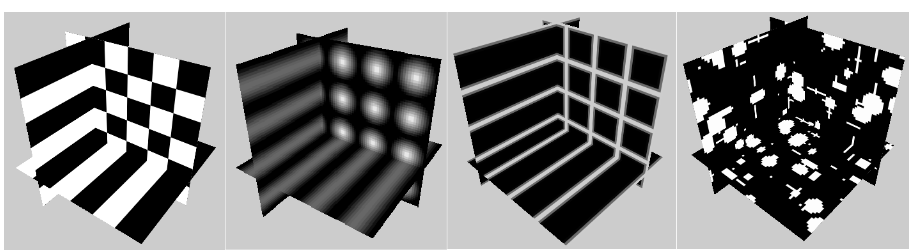


Fig. 4. Exemple of three-dimensional textured images made with geometric shape

To complete this database, we apply some transformations on each class of texture with translations and rotations according x, y and z axis. We can see some exemples of rotation results in Figure 5. Moreover, Gaussian noise and Gaussian blur are applied to increase variability in each existing three-dimensional texture class. Using this data base, we made three different databases that we use in classification experiments discribed in section 5. The first database is a set of three-dimensional texture images without any transformation (rotation, translation) or distorsion (noise). The second one contains additional gaussian noise. The last one is three-dimensional textures with random rotations according x, y and z axis.

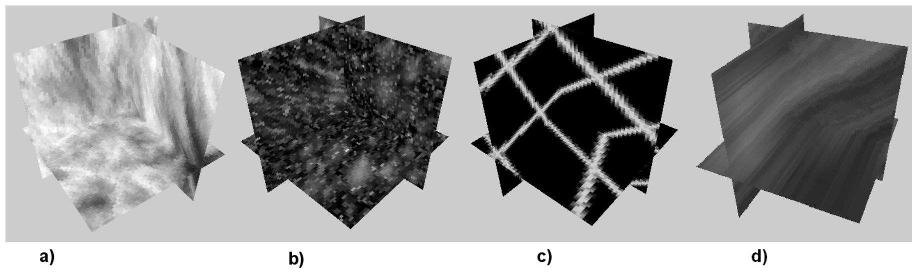
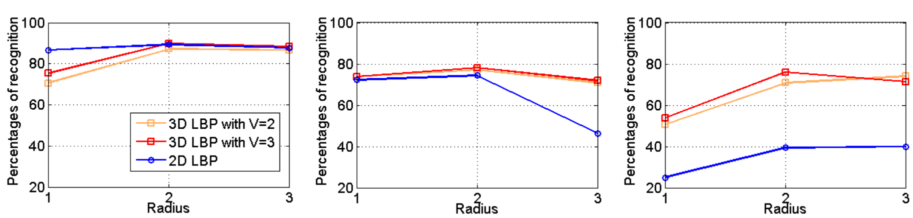


Fig. 5. Exemple of three-dimensional images with random rotation $(r1, r2, r3)$ according x, y and z axis. a)$(70°, 158°, 148°)$, b) $(34°, 22°, 141°)$, c) $(25°, 165°, 171°)$, d) $(0°, 0°, 47°)$

Each of these three databases contains 32 classes with 10 examples for each of them. For a class, 4 texture images are used for training the classifier, and the others are used as a testing set.

5.3 Classification results

Using the first database, we compare the performance of the two-dimensional and the three-dimensional Local Binary Pattern methods (Figure 6-a). We have seen that this database is a set of solid texture images without any transformation. As in [22], we test $LBP^{riu2}_{P',R}$ operator using three different spatial resolutions with three angular resolutions. For a given radius, if the number of vertex is too low, then the probability to obtain an uniform pattern decrease. In three dimensions, we compute the three operators $LBP^{riu2}_{26,1}$, $LBP^{riu2}_{98,2}$ and $LBP^{riu2}_{218,3}$ with $V \in \{2, 3\}$. In two dimensions, operators $LBP^{riu2}_{8,1}$, $LBP^{riu2}_{16,2}$ and $LBP^{riu2}_{32,3}$ are computed for each two-dimensional images in the plan (x, y) of the solid texture.



(a) Normal database (b) Noisy database (c) Database with rotation

Fig. 6. Percentages of recognition with two-dimensional and three-dimensional Local Binary Pattern method

Performance of two-dimensional and three-dimensional Local Binary Pattern are very close but better with the three dimensions method. However, the two-dimenional method shows more regular results according to parameters.

As before, performance of Local Binary Pattern method in two dimensions and three dimensions are compared using the second database (Figure 6-b). The second database is like the first one but contains additional gaussian noise. On this noisy database, three-dimensional method gives better results. With the third dimension, the information about the neighbourhood of a given central pixel is more significant. Consequently, the three-dimensional Local Binary Pattern is more robust to noise.

At last, Figure 6-c shows results obtained with the third database which is a set of solid texture with random rotation according x, y and z axis. As predicted, two-dimensional Local Binary Pattern method shows numerous classification errors and is unable to recognize three-dimensional oriented textures. To have more information with the two-dimensional approach, it should be necessary to conduct the two-dimensional study in many plans of different directions to consider the three dimensions.

6 Conclusion

Our purpose was to extend the Local Binary Pattern method to three dimensions and compare it with the two-dimensional model for classification of three-dimensional textures. We have also developed a freely available three-dimensional textures database for evaluation purpose. Using these images, we made classification experiments with a support vector machine (SVM) algorithm to compare the two-dimensional and the three-dimensional LBP methods. With the first database which is a set of three-dimensional texture images without deformation, three-dimensional Local Binary Pattern method allows to have a better percentage of recognition. However results obtained with the two-dimensional LBP are very close. Using the second database, two-dimensional LBP algorithm seems to be more sensitive to noise and gives lower percentage of recognition than the three-dimensional method. Indeed, with the third dimension, there is a better information about the gray level distribution that allows a better robustness to noise. At last, two-dimensional Local Binary Pattern method shows large classification error with the third database and is unable to detect three-dimensional oriented texture. In further research, it could be interesting to identify important textural features and merge them together to approach at best human perception.

References

1. Tuceryan, M., Jain, A.K.: 2.1. In: Texture Analysis. The Handbook of Patern Recognition and Computer Vision (1998) 207–248
2. Haralick, R.M.: Statistical and structural approaches to textures. Proceedings of the IEEE **67**(5) (1979) 786–804
3. Haralick, R.M., Shanmugam, K., Dinstein, I.: Texture features for image classification. IEEE Transactions on Systems, Man and Cybernetics **3**(6) (1973) 610–621
4. Wang, L., He, D.C.: Texture classification using texture spectrum. Pattern Recognition **23**(8) (1990) 905–910

5. Ojala, T., Pietikainen, M., Harwood, D.: A comparative study of texture measures with classification based on feature distributions. Pattern Recognition **29**(1) (1996) 51–59
6. Tuceryan, M., Jain, A.K.: Texture segmentation using voronoi polygons. IEEE Transactions On Pattern Analysis And Machine Intelligence **12** (1990) 211–216
7. Chellappa, R., Jain, A.K.: Markov Random Fields Theory and Application. Academic Press (1993)
8. Mosquera, A., Cabello, D., Carreira, M., Penedo, M.: A fractal-based approach to texture segmentation. In: ICIPA '92: Proceedings on the International Conference on Image Processing and its Application. (1992)
9. Turner, M.: Texture discrimination by gabor functions. Biological Cybernetics **55** (1986) 71–82
10. Mallat, S.G.: A theory for multiresolution signal decomposition: the wavelet representation. IEEE transaction on Pattern Analysis and Machine Intelligence **11** (1989) 674–693
11. Laine, A., Fan, J.: Textures classification by wavelet packets signatures. IEEE Transaction on Patern Analysis and Machine Intelligence **15** (1993) 1186–1191
12. Unser, M.: Texture classification and segmentation using wavelet frames. IEEE Transactions on Image Processing **4** (1995) 1549–1560
13. Stachowiak, G.P., Podsiadlo, P., Stachowiak, G.W.: A comparison of texture feature extraction methods for machine condition monitoring and failure analysis. Tribology Letters **20**(2) (2005) 133–147
14. Suzuki, M.T., Yoshitomo, Y., Osawa, N., Sugimoto, Y.: Classification of solid textures using 3d mask patterns. In: ICSMC '04: International Conference on Systems, Man and Cybernetics. (2004)
15. Kovalev, V.A., Petrou, M., Bondar, Y.S.: Texture anisotropy in 3d images. IEEE Transaction on Image Processing **8** (1999) 346–360
16. Ghoneim, D.M., Toussaint, G., Constans, J.M., de Certaines, J.D.: Three dimensional texture analysis in mri: a preliminary evaluation in gliomas. Magnetic Resonance Imaging **21** (2003) 983–987
17. Showalter, C., Clymer, B.D., Richmond, B., Powell, K.: Three-dimensional texture analysis of cancellous bone cores evaluated at clinical ct resolutions. Osteoporos Int **17** (2006) 259–266
18. Chen, X., Murphy, R.F.: Robust classification of subcellular location patterns in high resolution 3d fluorescence microscope images. In: EMBS'04 : Proceedings of the 26th Annual International Conference of the IEEE EMBS. Number 1-5 (2004)
19. Jafari-Khouzani, K., Soltanian-Zadeh, H., Elisevich, K., Patel, S.: Comparison of 2d and 3d wavelet features for tle lateralization. In: Proceedings of the SPIE. Volume 5369. (2004)
20. Zhan, Y., Shen, D.: Deformable segmentation of 3d ultrasound prostate image using statistical texture matching method. IEEE transaction on medical imaging **25**(3) (2006) 256–272
21. Zhao, G., Pietikäinen, M.: Dynamic texture recognition using local binary patterns with an application to facial expressions. IEEE Transaction on Pattern Analysis and Machine Intelligence **29**(6) (2007) 915–928
22. Ojala, T., Pietikäinen, M.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE transaction on Pattern Analysis and Machine Intelligence **24** (2002) 971–987
23. Chang, C.C., Lin, C.J.: LIBSVM: a library for support vector machines. (2001) Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.
24. Kopf, J., Fu, C.W., Cohen-Or, D., Deussen, O., Lischinski, D., Wong, T.T.: Solid texture synthesis from 2d exemplars. In: SIGGRAPH '07: Proceedings of the 34th International Conference and Exhibition on Computer Graphics and Interactive Techniques. (2007)
25. Gool, L.J.V., Dewaele, P., Oosterlinck, A.: Texture analysis anno 1983. Computer Vision, Graphics, and Image Processing **29**(3) (1985) 336–357