LOCAL BINARY PATTERNS USED ON CARDIAC MRI TO CLASSIFY HIGH AND LOW RISK PATIENT GROUPS

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ABSTRACT

In patients having suffered myocardial infarction, the myocardium does not function properly due to scarring. These patients are divided into high and low risk of getting arrhythmia using recognized risk markers like Left Ventricular Ejection Fraction (LVEF) and scar size. In Cardiac Magnetic Resonance (CMR) imaging, the scarred tissue in the myocardium is studied by increasing the intensity of scar area with the help of contrast agents. In this work, we have explored if a group of patients with high risk of getting arrhythmias (HAG) can be distinguished from a group of patients with low risk of getting arrhythmias (LAG) using the texture differences present in the scar tissue as inputs to a classifier. In this work, the textural differences of scarred myocardium tissue in HAG and LAG are captured using Local Binary Patterns (LBP). Automatic classification of HAG and LAG is important as patients with high risk of arrhythmia are identified and implanted with Implantable Cardioverter-Defibrillator (ICD). A non-parametric classification method is used to classify the LBP and contrast measure distributions of HAG and LAG. This is a preliminary work on the classification of HAG patients and LAG patients that has to be explored further. Even with a limited dataset, experiments show that HAG and LAG can be distinguished with a sensitivity of 75% and specificity of 83.33% using LBP.

***Index Terms*—** CMR image, Contrast measure, High and low risk arrhythmias, Local Binary Pattern, Scarred myocardium

1. INTRODUCTION

Cardiac Magnetic Resonance(CMR) imaging is used to examine the internal morphology of the heart. The myocardium, the muscular middle layer of the heart, gets scarred and without functioning properly after myocardial infarction. As a consequence, the left ventricular ejection fraction (LVEF) is reduced. The presented CMR images are Late Gadolinium (LG) enhanced images; i.e. contrast agents are used to increase the intensity of the scarred myocardium. The patients who suffered a myocardial infarction are differentiated into patients with high and low risk of getting life threatening irregular heart rhythms (ventricular arrhythmia) using recog-

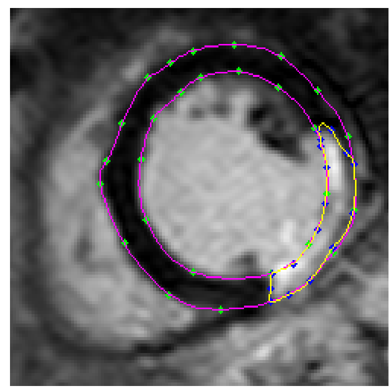
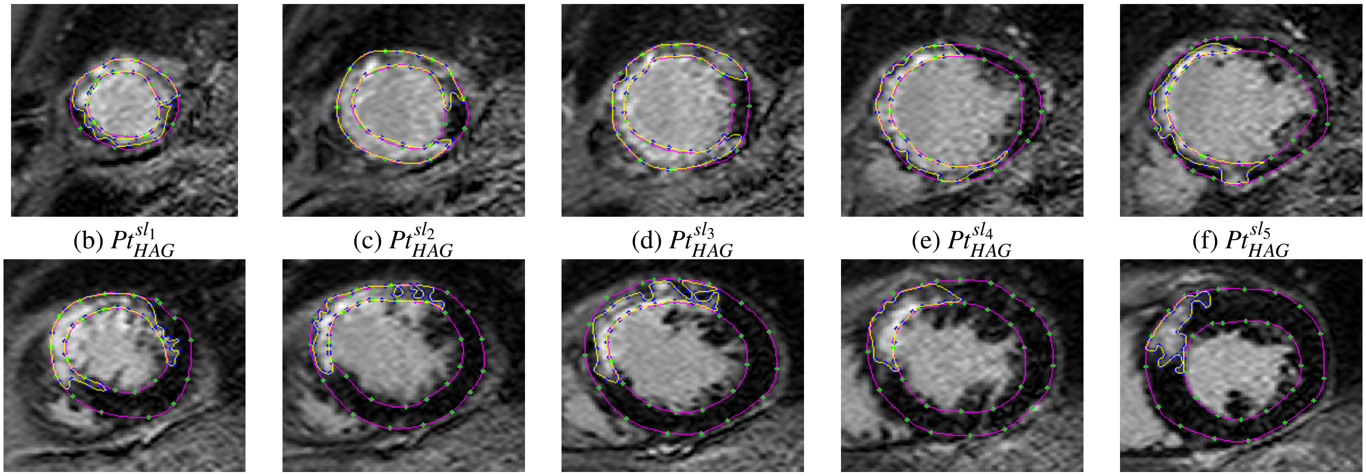


Fig. 1. Cropped short-axis CMR image showing manual segmentation of myocardium and scar tissues. The green and blue dots in the image are manually marked (by Cardiologist) coordinates to segment myocardium and scar. The magenta and yellow contours generated by cubic spline interpolations of the above coordinates show myocardium and scar tissues respectively.

nized risk markers like LVEF and scar size [1]. Patients with high risk of getting arrhythmia are inserted with Implantable Cardioverter-Defibrillator (ICD). An ICD is a small device that is placed in the patient's chest cavity to give electrical pulses or shocks to control a ventricular arrhythmia condition. Today, the decision on who is getting ICD implantation is based mostly on biological risk markers. Hence, improved strategies are required for the identification of patients who benefit most from ICD beyond the recognized risk markers due to the following concerns: (1) The ICD implantation procedure is expensive. (2) Overall benefit of ICD implantation for patients with low risk of arrhythmia is questionable. (3) The patients inserted with ICD can not undergo Cardiac Magnetic Resonance (CMR) imaging further.

A study by Yan *et. al*. [2], showed that scarred area contains useful information that assists in finding the high risk arrhythmia group (HAG) and low risk arrhythmia group (LAG)



(b) $Pt^{sl_1}_{HAG}$ (c) $Pt^{sl_2}_{HAG}$ (d) $Pt^{sl_3}_{HAG}$ (e) $Pt^{sl_4}_{HAG}$ (f) $Pt^{sl_5}_{HAG}$

(b) $Pt^{sl_1}_{LAG}$ (c) $Pt^{sl_2}_{LAG}$ (d) $Pt^{sl_3}_{LAG}$ (e) $Pt^{sl_4}_{LAG}$ (f) $Pt^{sl_5}_{LAG}$

Fig. 2. Row I and row II are the sequences of cropped CMR slices of HAG and LAG patients showing left ventricle with visible scar, respectively.

of patients. Information present in the scarred myocardium has to be utilized in order to classify the patients with high risk of getting arrhythmia after myocardial infarction. Engan *et. al*. [3], showed that texture features were able to classify the patients implanted with ICD into patients with high and low risk of getting arrhythmia using features that describe size, statistics and textures of the scarred myocardium. Recent studies showed that the scar tissue is heterogeneous in nature and that the mortality of patients with reduced LVEF depends on the heterogeneity of the scar tissue [4, 5]. This implies that scarred tissue might have different structures in HAG and LAG patients. The heterogeneity of the scar tissue can be captured using texture descriptors. Thus we believe that use of *appropriate texture descriptors* can be used to distinguish between HAG and LAG patients.

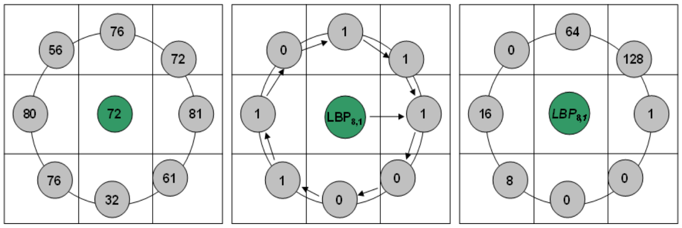
In this paper, we have explored the use of Local Binary Patterns (LBP) and contrast measure developed by Ojala *et. al*. [6] as the texture descriptors to investigate if these features can be appropriate in the context of classifying HAG from LAG patients. LBPs have been shown to work well in many biomedical applications [7, 8]. The experimental results show that scarred myocardium of HAG and LAG patients has textural differences; and that the two groups can be classified with 80% accuracy in some cases. The paper is organized as follows: Section 3 describes the LBP and contrast measures used as features in the following classification which is described in Section 4. Experiments and results are presented in Section 5, followed by conclusions with expected future work.

2. MATERIAL AND METHODS

The Department of Cardiology in Stavanger University Hospital provided LG enhanced CMR images of 24 patients with high risk of getting arrhythmia and 36 patients with low risk of getting arrhythmia. HAG consists of 24 patients implanted with ICD. The patients implanted with ICD cannot undergo CMR imagining further. LAG consists of 36 patients without ICD. LVEF and size of scar tissue were used in determining the patients in need of an ICD. All CMR images were obtained from an 1.5 Tesla MRI machine using the same protocol. These CMR images were stored according to the Digital imaging and communications in medicine (DICOM) format with 512×512 pixel resolution. The number of image slices with visible scar in each patient varies approximately from 5 to 12 depending on the size of scar and heart. Only short-axis image slices with visible scar were used in our experiments. The size of the scar varies from one slice to the next. Fig. 1 shows segmentation of healthy and scarred myocardium by experienced cardiologists superimposed on the original CMR image. Fig. 2 shows consecutive CMR slices of two patients belonging to HAG and LAG, respectively. The difference between HAG and LAG is not visually obvious from the CMR slices and toady's practice is to use risk markers like LVEF and scar size to differentiate between HAG and LAG patients. In this work we are concerned with exploring if the CMR images do contain information that can be useful in discriminating between HAG and LAG.

3. LOCAL BINARY PATTERN AND CONTRAST MEASURE

Local binary pattern (LBP) as introduced by Ojala *et. al* [6] is a powerful texture descriptor used in many computer vision applications because of its computation simplicity. The LBP image is obtained by replacing each pixel in the image with a label. The label is obtained by thresholding a neighborhood around the center pixel and then representing the thresholded



(a) (b) (c)

$LBP_{8,1} = 1\times2^0 + 0\times2^1 + 0\times2^2 + 1\times2^3 + 1\times2^4 + 0\times2^5 + 1\times2^6 + 1\times2^7 = 217$

Fig. 3. (a) Symmetric circular neighborhood of radius 1 with 8 samples around the center pixel. (b) Thresholding using the center pixel. (c) The LBP label is obtained by summing the thresholded string using powers of two as weights.

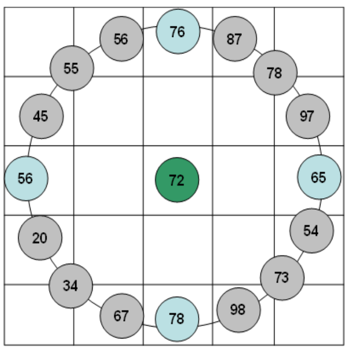


Fig. 4. Symmetric circular neighborhood of radius 2 with 16 samples around the center pixel. The samples that does not fall in the center of the gird (gray circles) are estimated by interpolation.

string as a binary number. The value of the label depends on the size of the neighborhood considered around the pixel. It can be represented as:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^P, \quad s(x) = \left\{ \begin{array}{l} 1,\ if\ x \geq 0; \\ 0,\ otherwise \end{array} \right\}, \tag{1}$$

where g_p and g_c are the gray level values of the neighborhood and center pixel, respectively. P represents the number of samples on the symmetric circular neighborhood of radius R. Fig 3 shows how to calculate LBP for circular neighborhood of radius 1 and eight samples (P=8). Fig 4 shows a circular neighborhood of radius 2 with 16 samples. The samples that do not fall on the grid are calculated using interpolation.

The LBP operator gives information about the distribution of the gray level values (pattern). In general, texture can be characterized by its gray level distribution and the strength of the distribution. The strength of the gray level distribution is an important feature for the human eye to distinguish various textures. Hence, a contrast measure is defined to find the strength of the pattern. The contrast is measured around the symmetric circular neighborhood as shown below:

$$VAR_{P,R} = \frac{1}{P}\sum_{p=0}^{P-1}(g_p - \mu)^2, \quad where\ \mu = \frac{1}{P}\sum_{p=0}^{P-1} g_p \tag{2}$$

Rotation invariant uniform LBP described in [9] is used for finding the LBP patterns in this work. If the number of bitwise transitions in LBP code is at most 2, then it is called uniform by Ojala *et. al*. [9]. The uniform LBP patterns are assigned to a single bin in the LBP histogram. Therefore, the number of bins for P sample points on the symmetric neighborhood is $P+2$ instead of 2^P because of the use of rotation invariant uniform LBP. Contrast measure is a continuous value and *VAR* histogram contains 64 bins for all P and R used in the experiments. LBP labels and contrast measure, *VAR* are calculated separately for each pixel in the scarred myocardium segmented by the cardiologists using different P and R. Fig 5 shows the calculation of the LBP labels of the scarred myocardium on all CMR slices of a patient and the histogram of the corresponding LBP values. The contrast measure, *VAR* is calculated in the same way as the LBP label. The *LBP* and *VAR* histograms calculated for the scarred myocardium are used further for the classification of HAG and LAG patients using a non-parametric classifier described in section 4.

4. NON-PARAMETRIC CLASSIFICATION

The statistics or the histogram of the LBP labels and contrast measure, *VAR* provide a description of the texture present in the image segment. For the classification of *LBP* or *VAR* histograms, non-parametric methods were used by Ojala *et. al* [6]. The *LBP* or *VAR* distribution of a test patient is called sample histogram. The model *LBP* or *VAR* histogram is obtained from a particular class of training patients. The sample and model LBP histogram distributions are classified using G-statistic [10]. It is defined as:

$$L(S, M) = -\sum_{b=1}^{B} S_b \, log \, M_b, \tag{3}$$

where S and M denote the sample and model *LBP* or *VAR* histogram distributions respectively. S_b and M_b are the probabilities of the bin b in the sample and model histograms. B is the total number of bins in the histogram. Chi square distance works better for smaller sample distributions [10]. It is defined as:

$$\chi(S, M) = \sum_{b=1}^{B} \frac{(S_b - M_b)^2}{S_b + M_b}, \tag{4}$$

The sample histogram is assigned to the class which gives the smallest distance when compared to the model histograms.

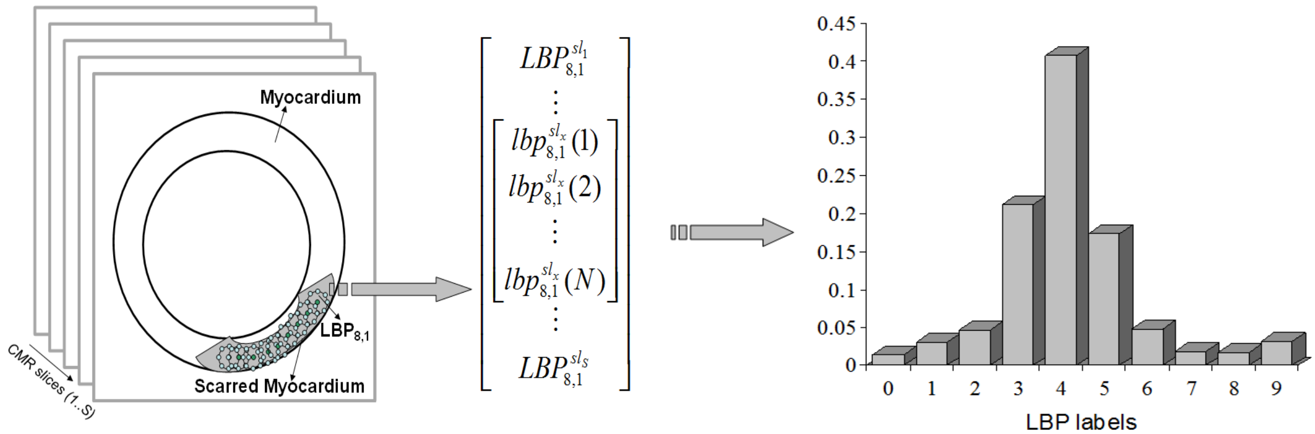


Fig. 5. The LBP values are calculated for each pixel in scarred myocardium using LBP operator, $LBP_{8,1}$. The LBP values are accumulated into a column vector from all the CMR slices (where scar is visible) belonging to a particular patient. $LBP_{8,1}^{sl_x}(N)$ is the LBP label of a pixel in scar region using $LBP_{8,1}$ operator, where N represents number of pixels in the scar region and x represents slice number in the CMR sequence belonging to a patient. The LBP histogram calculated from the accumulated LBP values is used to analyze the texture present in scarred myocardium.

The distributions obtained from LBP operators of varying P and R are combined to carry out multi-resolution analysis [9]. The dissimilarity measure for multi-resolution analysis is obtained by summing up the dissimilarity measures calculated from the distributions of respective LBP operators used in the analysis. It is given as:

$$L_N = \sum_{n=1}^{N} L(S^n, M^n), \tag{5}$$

where N is the number of LBP operators combined together. S^n and M^n correspond to the sample and model histograms extracted with n^{th} LBP operator, respectively.

5. EXPERIMENTS AND RESULTS

Experiments were conducted in MATLAB on the CMR images of HAG and LAG patients using LBP and contrast measure texture descriptors. In all the experiments, scarred myocardium segmented by cardiologists was used to find the LBP and contrast measure distributions. The HAG and LAG groups consists of 24 and 36 patients, respectively. In all patients, only short axis CMR slices with visible scar were used in the experiments.

LBP and contrast measure of scarred myocardium in HAG and LAG were calculated using MATLAB routines developed by Ojala *et. al.* [9]. LBP and contrast measure for each pixel in the scarred myocardium were calculated by changing the number of samples, P and radius, R of symmetric circular neighborhood. The LBP and contrast measure of each pixel in the scarred myocardium were accumulated on all the CMR slices belonging to a patient to find the *LBP* and *VAR* histograms. The LBP and contrast measure histograms were normalized on all the CMR slices of a patient.

Table 1. Classification accuracy (95% confidence interval) between HAG and LAG patients using LBP and contrast measure

Classification Accuracy (95% confidence interval) (%)		
P, R	$LBP_{P,R}$	$VAR_{P,R}$
4, 1	63.33 (50.6-74.3)	58.33 (45.7- 69.9)
8, 1	73.33 (60.9-82.9)	56.67 (44.1- 68.4)
8, 2	71.67 (64.5-85.5)	65 (52.3-75.8)
16, 2	73.33 (60.9-82.9)	65 (52.3-75.8)
16, 3	78.33 (66.3-86.8)	60 (47.3-71.4)
24, 3	80 (68.2-88.1)	60 (47.3-71.4)
24, 4	78.33 (66.3-86.8)	58.33 (45.7-69.9)

The calculation of the LBP histogram using the LBP operator, $LBP_{8,1}$ on all the CMR slices belonging to a patient is shown in Fig. 5. Multi-resolution analysis was experimented by combining information from two and three LBP operators of varying P and R. The dissimilarity measure for mutli-resolution analysis was calculated using the equation 5.

Leave-one-out strategy was used for classification in order to utilize the entire data available effectively. The model histograms were found by using all the patients in HAG and LAG leaving out one patient at a time. The histograms of all HAG and LAG patients in the training set were averaged to obtain the final model histogram for LAG and HAG. After finding the model histograms, the test patient, i.e. the patient left out, is classified using the non-parametric method described in section 4. The Chi-square distance method is used to find the distance between the sample and model histograms

Table 2. Classification accuracy between HAG and LAG patients using multi-resolution analysis of LBP operators

$LBP_{P1,\,R1+P2,\,R2}$	Classification Accuracy (95% confidence interval) (%)
$16,3;24,3$	80 (68.2-88.1)
$24,3;24,4$	78.3 (66.3-86.8)

$LBP_{P1,\,R1+P2,\,R2+P3,\,R3}$	Classification Accuracy (95% confidence interval) (%)
$8,1;8,2;16,3$	78.3 (66.3-86.8)
$8,2;16,3;24,3$	78.3 (66.3-86.8)

of HAG and LAG. Chi-square distance measure worked better than G-statistic in our experiments. The test patient is assigned to the class which gives less distance to the model histograms. The whole process is repeated for all the HAG and LAG patients. The classification accuracy with 95% confidence intervals using LBP and contrast measure is tabulated in table 1 for various P and R values.

The classification accuracy is the total number of correctly classified patients (HAG and LAG) using the cardiologists classification of HAG and LAG as a reference. This can of course be a topic of discussion since we would like to improve the decision strategy, not just duplicate it. The classification accuracy with LBP operator increases with the increase of radius and number of samples on the symmetric circular neighborhood. It is shown in [9] that the optimal LBP operator depends on the application. Table 1 shows that LBP performs better than the contrast measure, *VAR*. Table 2 shows the results of best combinations of LBP operators in multi-resolution analysis. However, with the given data set, classification could not be improved beyond 80% using multi-resolution analysis of LBP operators. The sensitivity and specificity of classifying the HAG and LAG patients are calculated for the LBP operator with high classification accuracy. Sensitivity is the ratio of true positives (HAG classified as HAG) to the sum of true positives and false negatives (HAG classified as LAG). Specificity is the ratio of true negatives (LAG classified as LAG) to the sum of true negatives and false positives (LAG classified as HAG). The sensitivity and specificity of classifying the HAG and LAG patients with the LBP operator, $LBP_{24,3}$ is 75% and 83.33%, respectively. This work is an initial step to explore the possibilities of classifying HAG and LAG using textural descriptors of scarred myocardium by LBP. Even with a limited dataset we obtained promising results that we want to explorer further. With help from complex classifiers like SVM, RVM, and a combination of various LBP descriptors we expect to improve the classification accuracy further.

6. CONCLUSION AND FUTURE WORK

This paper is an initial attempt to classify patients with high and low risk of getting arrhythmia entirely based on CMR images, using image processing techniques. LBP texture descriptors have been used to classify the LG enhanced CMR images of HAG and LAG patients. LBP and contrast measure are able to capture textural differences of scarred myocardium in HAG and LAG even with a limited data set. LBP and contrast measure were able to classify patients HAG and LAG with good classification accuracies with various parameter settings. The HAG and LAG patients can be classified with a sensitivity of 75% and specificity of 83.33% using $LBP_{24,3}$. The spatial pattern (*LBP*) performs better when compared to strength of the texture (*VAR*). It can be concluded that the spatial pattern of gray levels is an important feature to find the differences in the heterogeneity of scarred myocardium for classifying the HAG patients from LAG patients.

We want to further explore scarred myocardium with joint probabilities of LBP and contrast measure [9] as well as combining these features with other features, for example recognized risk markers like LVEF and scar size, in a more complex classifier. One problem of testing such a combined classifier is that our data material is classified into HAG and LAG groups based upon LVEF, thus we would need a different study material or a different way of defining true HAG and LAG patient groups prior to testing.

7. REFERENCES

[1] A. Moss, W. Zareba *et al.*, "Prophylactic implantation of a defibrillator in patients with myocardial infarction and reduced ejection fraction," *The New England Journal of Medicine*, pp. 877–883, 2002.

[2] A. Yan, A. Shayne *et al.*, "Characterization of peri-infarct zone by contrast-enchanced cardiac magentic resonance imaging is a powerful predictor of post-myocardial infarction mortality," in *Pro. MICCAI 2004*, vol. 114. Circulation, 2006, pp. 32–39.

[3] K. Engan, T. Eftestøl, S. Ørn, J. Kvaløy, and L. Woie, "Exploratory data analysis of image texture and statiscal features on myocardium and infarction areas in cardiac magnetic resonance images," in *Pro. EMBS 2010*. IEEE, 2010, pp. 5728–5731.

[4] A. Schmidt, C. F. Azevedo *et al.*, "Infarct tissue heterogeneity by magnetic resonance imaging identifies enhanced cardiac arrhythmia susceptibility in patients with left ventricular dysfunction," in *Circulation*, vol. 115. American Heart Association, 2007, pp. 2006–2014.

[5] S. D. Roes, C. J. W. Borleffs *et al.*, "Infarct tissue heterogeneity assessed with contrast-enhanced MRI predicts spontaneous ventricular arrhythmia in patients with ischemic cardiomyopathy and implantable cardioverter-defibrillator," in *Circ Cardiovasc Imaging*, vol. 2. American Heart Association, 2009, pp. 183–190.

[6] T. Ojala, M. Pietikainen *et al.*, "A comparative study of texture measures with classification based on feature distributions," *Pattern Recognition*, vol. 29.

[7] L. Nanni, A. Lumini, and S. Brahnam, "Local binary pattern variants as texture descriptors for medical image analysis," *Artificial Intelligence in Medicine*, vol. 49.

[8] B. Li and M. Meng, "Texture analysis for ulcer detection in capsule endoscopy images," *Image Vis. Comput.*, vol. 27.

[9] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *Pattern Analysis and Machine Intelligence*, vol. 24, pp. 971–987, 2002.

[10] M. Pietikäinen, G.Zhao *et al.*, *Computer Vision Using Local Binary Patterns*. Springer, 2011, vol. 40.