An Image Processing Approach for Marble Classification

Hussein R. Al-Zoubi[1,a], Mahmood A. Al-Khassaweneh[1,b], Ibrahim A. Altawil[2,c]

[1]Department of Computer Engineering, Yarmouk University, Irbid, Jordan
[2]Department of Electrical Power Engineering, Yarmouk University, Irbid, Jordan
[a]e-mail: halzoubi@yu.edu.jo
[b]e-mail: khassaweneh@yu.edu.jo
[c]e-mail: ialtawil@yu.edu.jo

Abstract— This paper briefly reviews recent research in the area of texture classification with a focus on the problem of marble classification, and proposes a simple approach for this purpose. It aims at the automatic analysis and classification of marbles and granites. This is an important requirement for this field of industry in today's life and in the future, into groups according to quality: Class A excellent, Class B good, and Class C fair. The proposed approach consists of two phases: training and classification. In the training phase, we apply the k-means clusters unsupervised learning method to categorize large number of marble samples into three classes A, B, and C. The output of the first phase is a set of thresholds used as inputs for the second phase. For classification, we have used Sobel edge detector. Experimental results show that the proposed approach can achieve promising practical results.

Keywords— k-Means clustering, marble classification, Sobel edge detector, texture analysis.

I.   INTRODUCTION

Marble, granite, and ceramic tiles are often used for decorative purposes. This imposes two basic quality features, appearance constancy and material strength, to exist in these materials [1]. The process of marble classification is usually performed by a human expert. This process tends to be difficult and error prone [2]. Automatic inspection and classification of color textures are one of the most important machine-vision applications [3]. Marbles and granites are natural textures on which we can apply machine-vision techniques using image processing for the purpose of automatic inspection and classification.

The automatic classification and quality control in general [4] and particularly of marbles and granites increase the homogeneity of the product supplied by factories, and reduce time, cost, and discrepancies in the marble industry [5]. The value of marbles in construction markets can change according to their colors and textural characteristics [6]. In general, defects in marble and granite materials can be divided into two basic categories: blob-like and thin structures, or cracks [3]. We can utilize these facts when designing an expert system for the automatic classification of marbles.

However, the analysis and classification of rock textures are generally considered difficult tasks because in many cases they are non-homogenous and strongly directional. In addition, the granular size and color of these textures may vary significantly [7]. The authors of [8] also add that the realization of an expert system that automatically executes such control is a challenging problem since the appearance of these materials may be very similar; and their classification may be difficult even for a human observer. In this paper, we present a simple approach for marble classification using image processing techniques.

An extensive research has been performed in the area of texture classification. For example, in [9]-[11], the authors compare and contrast between color histograms and texture features for the purpose of color texture classification where they get to the conclusions that either color or texture alone gives better classification accuracy than the joint color texture features.

The authors illustrate that color histograms are better under stable illumination conditions, while the texture features, especially the multiresolution local binary pattern distributions, show better performance irrespective of illumination.

In [12], color texture classification was performed using single and multi-channel co-occurrence matrices. The author gets to the results that separate analysis of texture by intensity pattern analysis and of color by histogram is preferred according to RGB color space, while intensity independent color patterns are shown to exist using integrative color features based on the LUV color space. In [13], the authors focus on the one-class classification problem, also called outlier rejection. Different from the multi-class classifiers, the one-class classifier, given an object, decides if it belongs to the target class or it is an outlier. The proposed classifier was designed for forming a class with required homogeneity in the coordinated clusters representation (CCR) feature space using gray-level texture images of Brodatz, Rosa, and Porrino texture databases.

The authors of [14] applied the ultrasonic method to measure crack depths that exist in marble statues. The proposed approach studied the Michelangelo's David statue as a case study. Results showed the ability to detect deteriorations in surfaces and diffuse cracks. A metric called block quality designation (BQD) ratio was proposed in [15] to assess rock mass in the marble industry. In [16], a design system was proposed to generate images of marbling textile patterns.

The rest of the paper is organized as follows: Section 2 gives background about the image processing techniques used in the proposed algorithm. Section 3 explains in details the proposed approach. In Section 4, the proposed algorithm is tested through a series of simulations. Finally, we conclude the paper in Section 5.

II. BACKGROUND

The RGB (red, green, blue) is one of many color models in use today in the realm of digital image processing. Each RGB color pixel in a 24-bit RGB color image is said to have a depth of 24 bits (8 bits for red, 8 bits for green, and 8 bits for blue colors). The total number of colors in a 24-bit RGB image is $(2^8)^3 = 16,777,216$ [17].

Image segmentation subdivides an image into its constituent regions or objects [17]. Let the RGB vector a denotes the average color that we wish to segment. Let z denote an arbitrary point in RGB space. The Euclidean distance between z and a is given by [17]:

$$D(z,a) = \|z - a\| = [(z-a)^T(z-a)]^{\frac{1}{2}} = [(z_R - a_R)^2 + (z_G - a_G)^2 + (z_B - a_B)^2]^{\frac{1}{2}} \qquad (1)$$

where the subscripts R, G, and B denote the RGB components of vectors a and z. z is said to be similar to a if the Euclidean distance between them is less than a specified threshold, D_0. Image segmentation based on thresholding is very common in many applications. The intensity histogram of a 24-bit RGB image is the discrete function $h(r_k) = n_k$, where r_k is the kth intensity value, $0 \leq k \leq 255$ and n_k is the number of pixels in the image with intensity r_k [17]. If the intensity histogram is drawn for an image $f(x,y)$ composed of a light object on a dark background, then the segmented image, $g(x,y)$, is given by [17]:

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > T: \text{object point} \\ 0 & \text{if } f(x,y) \leq T: \text{background point} \end{cases} \qquad (2)$$

Erosion and dilation are two fundamental morphological image processing operations. With A and B as sets in Z^2, the erosion of A by B, denoted A $\ominus$ B, is the set of all points z such that B, translated by z, is contained in A, and is defined as [17]:

$$A \ominus B = \{z | (B)_z \subseteq A\} \tag{3}$$

The dilation of A and B, on the other hand, is the set of all displacements, z, such that $\widehat{B}$ and A overlap by at least one element, and is defined by:

$$A \oplus B = \{z | (\widehat{B})_z \cap A \neq \emptyset\} \tag{4}$$

where $\widehat{B}$ is the reflection of B; that is, the set of points in B whose (x, y) coordinates have been replaced by $(-x, -y)$ and is defined by:

$$\widehat{B} = \{w | w = -b, b \in B\} \tag{5}$$

A. The Sobel Edge Detector

The Sobel operator [18] is one of the well-known algorithms in image processing for edge detection by performing a 2-D spatial gradient measurement on an image I. The computations are performed using two 3×3 convolutional kernels as follows:

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * I \tag{6}$$

$$G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I \tag{7}$$

where G_x and G_y are two matrices containing the horizontal and vertical derivative approximations, respectively, and the $*$ denotes the 2-D convolution. The gradient magnitude can be calculated by:

$$G = \sqrt{G_x^2 + G_y^2} \tag{8}$$

The gradient direction can also be calculated by:

$$\theta = tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{9}$$

B. k-Means Clustering Algorithm

The k-means clustering algorithm [19] is one of the well-known unsupervised learning algorithms. It is an efficient and simple algorithm for partitioning data into k clusters. The algorithm works on minimizing the Euclidean distance of (2). Initially, the algorithm picks k samples randomly from the data set to represent the means of the k clusters. Then, each sample in the data set is placed in a certain cluster based on the Euclidean distance between that sample and the cluster mean. The mean for each cluster is then recomputed after all the

samples have been placed in a cluster. The process is repeated for several iterations. If the difference between the output of the current iteration and the previous iteration is less than a preset threshold, the algorithm terminates.

III.   THE PROPOSED APPROACH

The proposed approach consists of two phases: Training and Classification. The purpose of the first phase is to get appropriate values to be used as thresholds during the classification phase. In our classification system, we have employed Sobel edge detection approach to classify marbles.

The classification approach proposed by this method consists of several steps. Fig. 1 illustrates these steps, and can be summarized as follows:

1. The image of the sample marble to be classified is loaded. We have used a standard image size of 352×288 pixels. This size is used in the well-known common intermediate format (CIF) for image sequences.
2. The gray-level image is generated from the colored image of the previous step. Fig. 2 (a), (b), and (c) show the gray-level image of three marble samples.
3. A binary image is obtained from the gray-level image.
4. The Sobel edge detector is applied on the binary image of the previous step. The images classified by the Sobel edge detector are shown in (d), (e), and (f) of Fig. 2, where (d) corresponds to (a), (e) to (b), and (f) to (c).
5. The output image obtained after applying the Sobel edge detector is then cleaned by opening and closing through erosion and dilation. The purpose of this step is to eliminate any noise (isolated pixels).
6. The number of ON (white) pixels is counted. The number of ON pixels for the samples shown in Fig. 2 is 101 for (a), 1797 for (b), and 6752 for (c).
7. The value obtained in Step 6 is compared against Threshold values. An image is placed in a certain class according to weather it has ON pixels above or below thresholds. The threshold values are obtained by applying the k-means clustering to a training set of marbles.
8. The sample is placed in the category with the closest threshold. The sample image (a) of Fig. 2 is classified as Class A, (b) is classified as Class B, and (c) is classified as Class C.

The colored sample image is converted to a gray-level image, then to a binary image, on which Sobel edge detection is applied. After that, dilation and erosion are performed, and the number of ON pixels is calculated. Finally, a classification decision is taken based on the number of ON pixels.
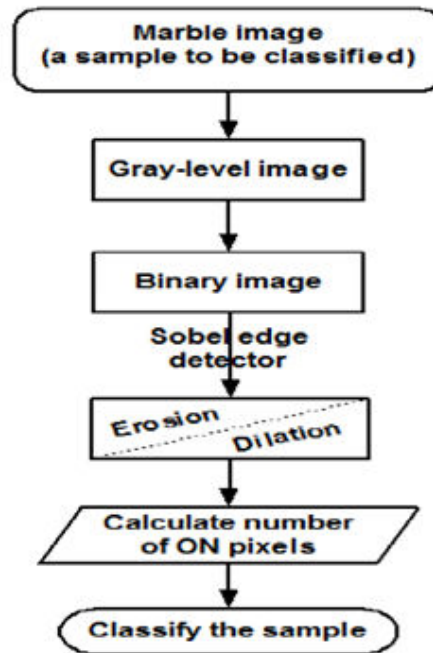
Fig. 1. The process followed by classifying marbles using edge detection

The overall classification process is illustrated by Fig. 3. In the first phase of the proposed approach, a large number of sample marble images is used for training purposes. Each sample image undergoes through the Sobel edge detector to get the number of ON pixels for that sample. The number of ON pixels for all the samples in this phase is used as an input for the k-means clustering algorithm to classify the samples into three classes. Thresholds are defined as the boundaries between the three classes obtained from the k-means clustering algorithm. The output of the k-means cluster algorithm is used to assign the threshold values used to classify the samples into classes A, B, and C later in the testing phase. Every sample used in the first phase is also applied to an expert human inspection to validate the classification results of the proposed algorithm.
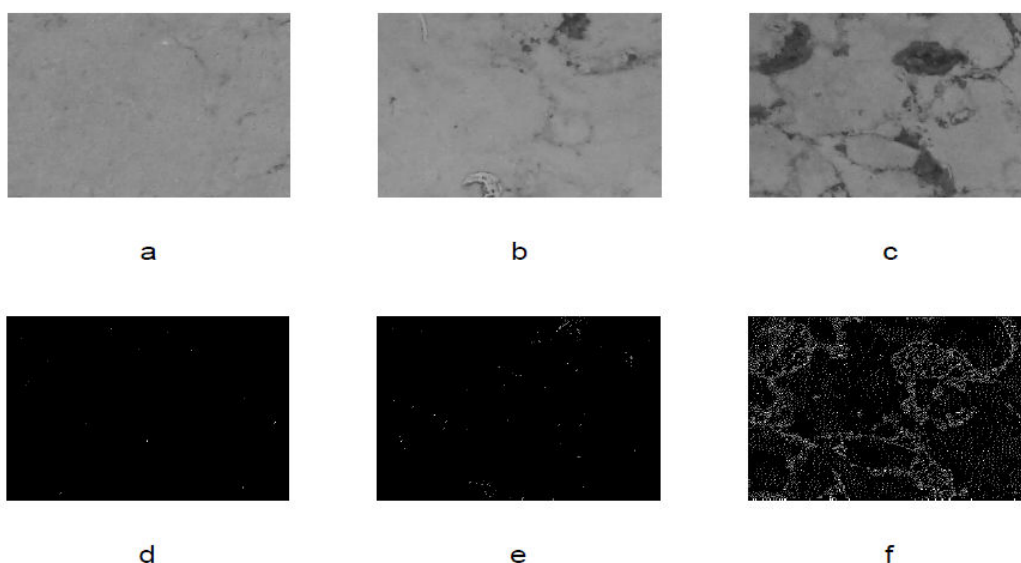

Fig. 2. Marble samples. Gray-level images are shown in (a), (b), and (c). The images classified by the Sobel edge detector are shown in (d), (e), and (f), where (d) corresponds to (a), (e) to (b), and (f) to (c). The white pixels in (d), (e), and (f) are the ON pixels which are used for classification after erosion and dilation

Phase II represents the normal job of the classification process. Every new marble sample to be classified undergoes through the Sobel edge detector using the threshold values obtained during Phase I. Through an extensive number of experiments, the proposed classification system has proved to be simple, fast, and reliable as it will be illustrated by the next section.
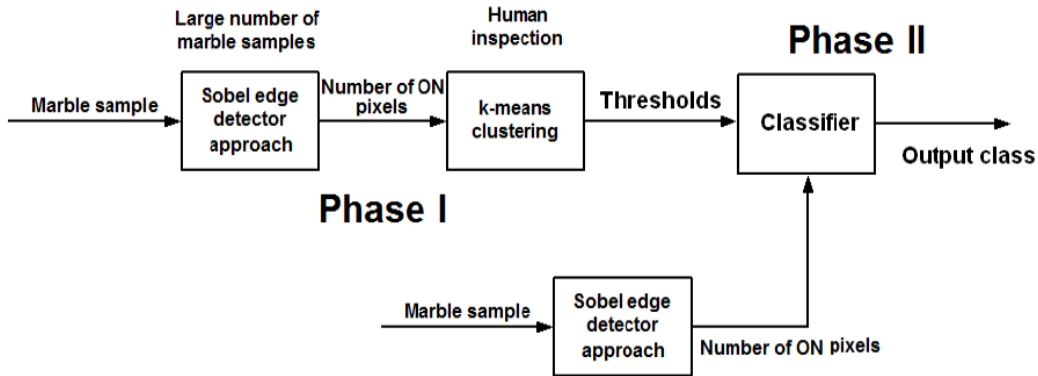

Fig. 3. The overall classification process

IV.   SIMULATION RESULTS

In order to test the effectiveness of the proposed approach, many simulations have been carried out. A large number of samples has been used. Fig. 4 shows the number of ON pixels (normalized) for 60 samples. As the number of ON pixels decreases, the quality of the sample gets better. In order to classify the samples into three classes; Excellent: A, Good: B and Bad: C, thresholds obtained by applying the k-means clustering have been used. Another set of pictures, consisting of 96 pictures, has been used for testing. Fig. 5 shows the output of the proposed classification method for 12 chosen samples. Four images are classified as A, three as B and five as C.

In order to verify the correctness of these results, these samples were shown to human experts to classify them according to their experiences. Table 1 shows the comparison results. The output of the proposed algorithm and expert decision agrees on 93 out of 96 samples. The only disagreement is on samples (7), (40), and (77) because they lie on the borders between the different classes. Therefore, for those samples, which lie close to the thresholds, the decision of the human expert should be considered.

In comparison with the state-of-the art research, our proposed approach achieves comparable, or even better results. For example, the authors of [8] achieved an average classification success ratio of 91.85 %, while 96.88 % of our images have been classified successfully as Table 1 shows. Moreover, the proposed method of [20] degrades as the textured patterns becomes less regular, whereas our proposed method performs well for different textured patterns as shown in Fig. 5.

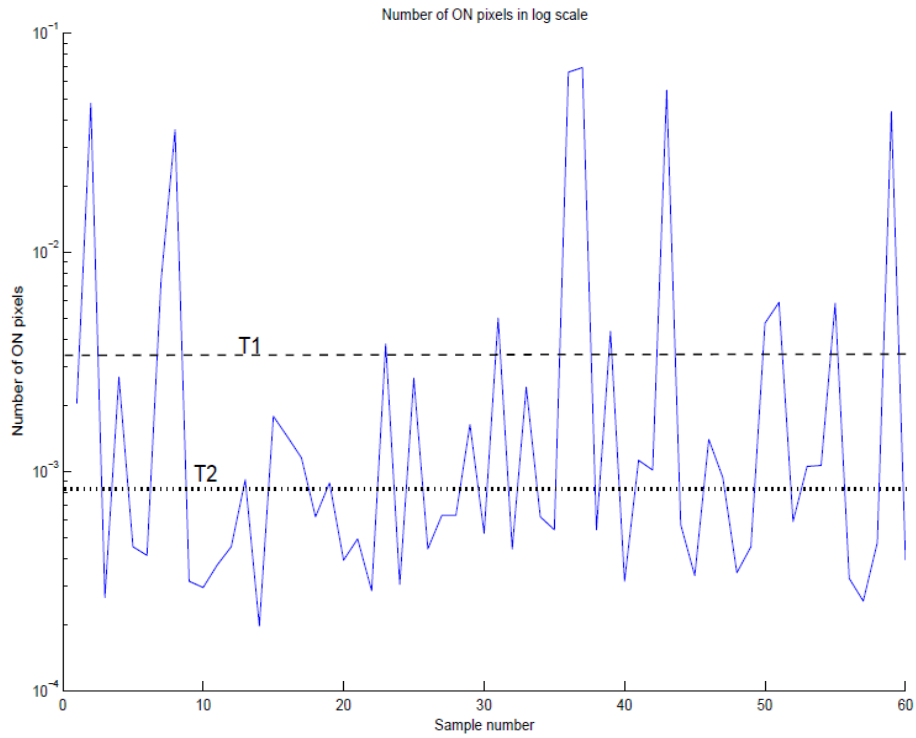Fig. 4. The number of ON pixels (normalized) in log scale. T1 and T2 represent the thresholds used for classification
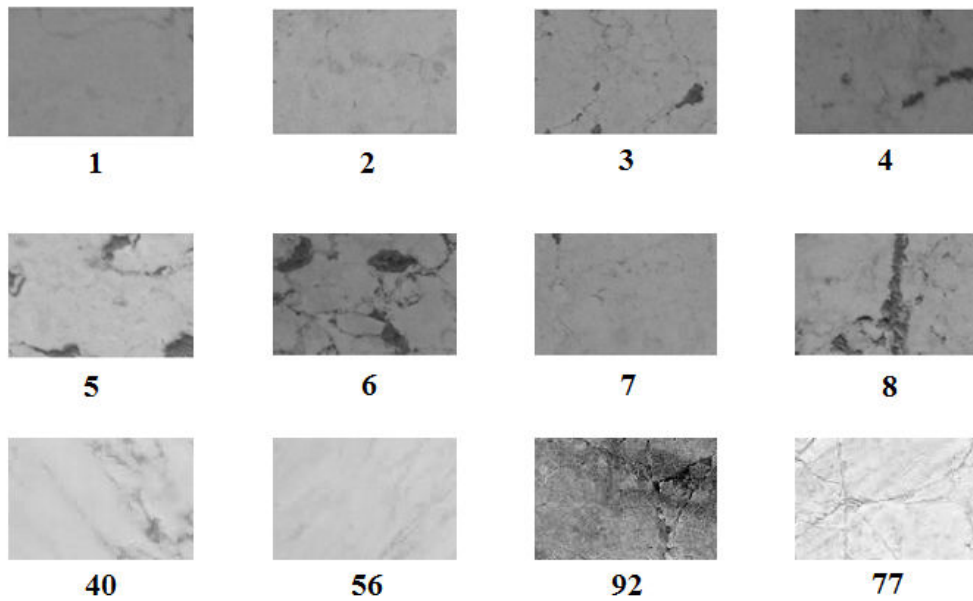

Fig. 5. The output of the proposed classification method applied on different marble samples. Samples shown in (1), (2), (40) and (56) are classified as A. Samples shown in (3), (4) and (7) are classified as B. Samples shown in (5), (6), (8), (77) and (92) are classified as C

TABLE 1
COMPARISON BETWEEN THE OUTPUT OF THE PROPOSED METHOD AND THE EXPERT DECISION

Sample #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Proposed	A	A	B	B	C	C	B	C	C	A	C	B	B	C	A	A	C	B	B	B	A	A	A	A
Expert	A	A	B	B	C	C	A	C	C	A	C	B	B	C	A	A	C	B	B	B	A	A	A	A
Sample #	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
Proposed	C	A	A	A	B	B	A	A	A	A	A	B	B	B	C	A	A	A	A	B	A	A	A
Expert	C	A	A	A	B	B	A	A	A	A	A	B	B	B	C	B	A	A	A	B	A	A	A
Sample #	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72
Proposed	A	B	B	B	A	A	A	A	A	A	A	C	A	A	A	B	A	C	A	A	A	A	A
Expert	A	B	B	B	A	A	A	A	A	A	A	C	A	A	A	B	A	C	A	A	A	A	A
Sample #	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96
Proposed	A	A	B	B	C	A	A	A	A	A	A	A	A	A	A	A	A	A	C	A	A	B	A
Expert	A	A	B	B	B	A	A	A	A	A	A	A	A	A	A	A	A	A	C	A	A	B	A

V. CONCLUSION

Image processing and machine vision are two complementary fields, which can be employed in many areas including industrial automation and robotics. This research investigates a problem from the industrial sector. In this paper, we propose a simple but yet efficient marble classification method. The proposed method consists mainly of two phases: training and testing. In Phase I, the k-means cluster technique is utilized to get threshold values that can be used in the classification process. In addition, the Sobel edge detector is applied to obtain the pixels that are likely to lie in defected areas, and therefore act as an indicator of the quality of the marble being tested. The algorithm has been tested on a large number of samples; and the results highly agree with the human expert decision. The success rate exceeds 96%. Moreover, experimental results show that the proposed approach is comparable, or even outperforms the state-of-the-art methods.

REFERENCES

[1] M. Selver, E. Ardali, O. Onal and O. Akay, "Predicting uniaxial compressive strengths of brecciated rock specimens using neural networks and different learning models," *Proc. of the IEEE International Symposium on Computer and Information Sciences*, pp. 1-4, 2008.

[2] M. Murakami, M. Yamagiwa and M. Uehara, "Decision model for a system to start communicating with a human," *International Journal of Computer Systems Science and Engineering*, vol. 25, no. 2, 2010.

[3] J. Kittler, R. Marik, M. Mirmehdi, M. Petrou and J. Song, "Detection of defects in colour texture surfaces," *Proc. of the IAPR Workshop on Machine Vision Applications*, pp. 558-567, 1994.

[4] W. A. Halang, "Automated control systems for the safety integrity levels 3 and 4," *International Journal of Computer Systems Science and Engineering*, vol. 24, no. 1, 2009.

[5] J. Martinez-Alajarin, J. Luis-Delgado and L. Tomas-Balibrea, "Automatic system for quality-based classification of marble textures," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 35, no. 4, pp. 488-497, 2005.

[6] M. K. Gokay and I. B. Gundogdu, "Color identification of some Turkish marbles," *Construction and Building Materials*, vol. 22, no. 7, pp. 1342-1349, 2008.

[7] L. Lepisto, I. Kunttu, J. Autio, and A. Visa, "Rock image classification using non-homogenous textures and spectral imaging," *Proc. of WSCG Short Papers*, pp. 82-86, 2003.

[8] F. Bianconi and A. F. Alvarez, "Granite texture classification with gabor filters," *In Actas del XVIII Congreso Internacional de Ingenieria Grafica*, 2006.

[9] M. Pietikainen, T. Maenpaa and J. Viertola, "Color texture classification with color histograms and local binary patterns," *Proc. of the International Workshop on Texture Analysis and Synthesis*, pp. 109-112, 2002.

[10] T. Maenpaa, M. Pietikainen and J. Viertola, "Separating color and pattern information for color texture discrimination," *Proc. of the IEEE International Conference on Pattern Recognition*, pp. 668-671, 2002.

[11] T. Maenpaa and M. Pietikainen, "Classification with color and texture: jointly or separately," *Pattern Recognition*, vol. 37, no. 8, pp. 1629-1640, 2004.

[12] C. Palm, "Color texture classification by integrative co-occurrence matrices," *Pattern Recognition*, vol. 37, no. 5, pp. 965-976, 2004.

[13] R. Sanchez-Yanez, E. Kurmyshev and A. Fernandez, "One-class texture classifier in the CCR feature space," *Pattern Recognition Letters*, vol. 24, no. 9-10, pp. 1503-1511, 2003.

[14] G. Pascale and A. Lolli, "Crack assessment in marble sculptures using ultrasonic measurements: laboratory tests and application on the statue of David by Michelangelo," *Journal of Cultural Heritage*, In press, available online 13 March 2015.

[15] H. Elci and N. Turk, "Rock mass block quality designation for marble production," *International Journal of Rock Mechanics and Mining Sciences*, vol. 69, pp. 26-30, 2014.

[16] S. Lu, P. Y. Mok and X. Jin, "From design methodology to evolutionary design: an interactive creation of marble-like textile patterns," *Engineering Applications of Artificial Intelligence*, vol. 32, pp. 124-135, 2014.

[17] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Third Edition, Pearson Education Inc., 2008.

[18] I. Sobel and G. Feldman, "A 3×3 isotropic gradient operator for image processing," *Presented at a talk at the Stanford Artificial Project*, 1968.

[19] J. B. MacQueen, "Some methods for classification and analysis of multivariate observations," *Proc. of Berkeley Symposium on Mathematical Statistics and Probability*, vol. 1, pp. 281-297, 1967.

[20] D. M. Tsai and T. Y. Huang, "Automated surface inspection for statistical textures," *Image and Vision Computing*, vol. 21, no. 4, pp. 307-323, 2003.