A Generic System for The Classification of Marble Tiles Using Gabor Filters

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***Abstract*—This paper presents a marble tile feature extraction system which can be easily used for any classification system. Our system employs Gabor filtering and other image processing techniques to differentiate between different marble textures. As a final product of the system, the percentages of veins, spots, and swirls on the marble images are calculated. Therefore, the presented system can be considered as the core engine of a very portable marble tile classification system. This paper also presents a new verification method which is based on satisfying the inter-expert variability. Experiments on 40 different marble tiles are performed and we concluded that the presented system can be reliably employed for the measurement of the marble features in real life.**

I. INTRODUCTION

Marble is formed with a process that requires complex geological phases under very high pressures and temperatures over many millions of years. White and homogenous marble is the result of metamorphism of very pure limestone. When other material is involved in the marble formation process, the homogenous structure disappears and veins, spots, and swirls show up as textures on polished tiles (Fig. 1). If these tiles are arranged carefully on building surfaces, they create esthetic environments with a very unique and pleasing appearance. Hence, the market for textured marble slabs is huge and constantly growing.

Although the marble mining and processing business is vastly automated, the classification and arrangement of textured marble tiles are still done by expert human operators. The manual classification has some severe problems such as slow classification rates, fatigue, boredom, subjectivity, and need for training. Automatization of the visual classification would be very beneficial. Computerized inspection and classification of textured marble tiles are some of the most challenging problems of industrial computer vision. The fact that inspected material is not human-made makes this task an unconstrained problem. The other major problem with marble tile classification systems is the difficulty of validation and verification of these systems. For a considerable rate of cases, different human experts frequently assign different classification labels to the same tile if there are more than three classes. Since there is no ground truth data other than human expert opinions, a decision tree based training and verification process becomes unpractical. Novel verification methods need to be developed.

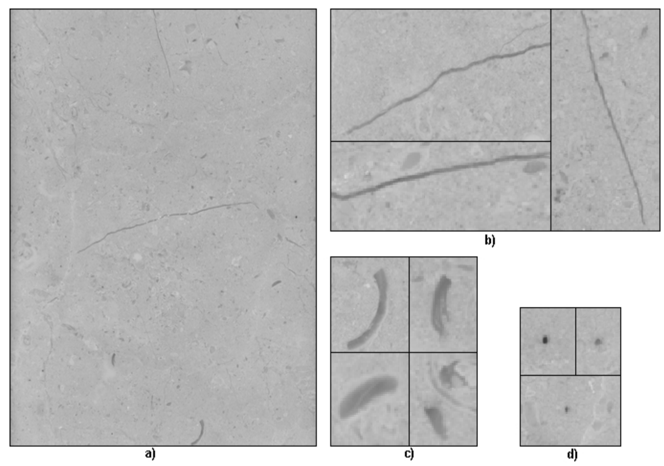

Fig. 1. A sample marble tile with veins, spots, and swirls: a)the complete original image, b)image sections containing veins, c)image sections containing swirls, d)image sections containing spots.

There are some systems reported in the literature to address the marble tile classification problem. Martinez-Alajarin and Tomas-Balibrea [1] presented a system which classifies marble slabs according to their color texture features. This system uses HSI space for texture analysis. The texture recognition algorithm called sum and difference histograms (SDH) [2] is used to extract texture dependent features of the slab image, which is fed to a LVQ network [3] to obtain the marble slab classes. The system assumes a fixed number of classes, which cannot be changed without retraining the system. The properties for each class is also fixed and cannot be changed by the users.

Luis-Delgado *et. al.* [4] have proposed a methodology based on the wavelet decomposition for the analysis and classification of images of marble surfaces according to their visual quality parameters. Classification of marble slabs resulted in three quality categories which are extra, commercial and low.

Martinez-Alajarin *et. al.* [5] presented a system for the classification of marble slabs into different groups in realtime. System starts with texture analysis performed by SDH with different color spaces then a feature extraction process is applied with principal component analysis. At the end they train a multi layer perceptron neural network with back propagation algorithm to classify the marble slabs into three quality categories.

None of the above systems offer to the user any way of in-field customization because these systems need training which has to be done by the system experts. This is a huge drawback for practical use because the classification of marbles needs to be adjusted by considering the customer requests and by inspecting the texture type of the marbles arriving from the mines.

The types of marbles produced around the world are very different, which makes it difficult to design a general classification system. Furthermore, the needs of customers also change constantly which requires addition and modifications of classes. Moreover, classification is done not only for quality assurance but also for texture grouping. Therefore, it can be argued that any system with a fixed number of classes and class features are not very practical for the general marble classification task. This is a severe problem especially in Turkish marble industry around Bilecik region. The marble tiles produced in this region are never without any texture. In fact, marble tiles with different textures on their surface is intensively demanded in the world markets. Therefore, these textural features gains significant importance on marble tile classification systems. So these textural features must be extracted from marble and grouped together. This process needs enhanced specialized techniques to be developed for quality classification based on texture amount rather than SDH used in [3], [5].

This paper presents a system that is highly customizable by the user. The main idea of the system is to assign scores for each tile in terms of veins, spots, and swirls. The assigned values can be easily used for classification by appropriate machine learning methods or by the end user using simple thresholding. We also introduce a novel verification method for the marble texture measurement system. This method uses the manual measurement results from a number of human experts and compares them with each other. The results of the system generated measurements are also compared with the experts and we seek to reach the inter-expert variability.

The main contributions of this paper are summarized as follows:

- The system extracts intuitive features of the marble tiles that can be easily used for texture classification by the end-user.
- The system does not include any training steps to produce the marble classes. This makes our system highly customizable, because classification can be reduced to simple thresholds in three dimensions.
- A novel application of Gabor filtering produces information about the amount of veins, spots, and swirls in the marble tile.
- The number of classes is not constrained by the system. It can be adjusted by the end user.
- A novel verification method that measures inter-expert variation is proposed to show that the system performance is as good as a human expert.

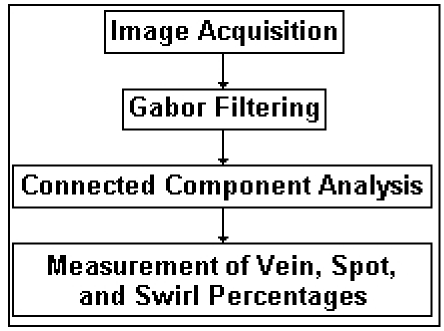

Fig. 2. System model of the proposed system.

Note that this paper does not define a specific classification system for the marble tiles. The main results from the system is a set of intuitive marble tile feature measurements of the percentage of veins, spots, and swirls. These measurements can be easily employed by a classification system to obtain the end results. Therefore, the presented system can be considered as the core engine of a very portable marble tile classification system.

The organization of this paper is as follows. In Section II, the proposed system was introduced with all the phases. In Section III, experimental results from the proposed system are compared with results of the human experts. In Section IV, we provide concluding remarks.

II. SYSTEM OVERVIEW

This section describes overall structure of the system. The main phases of the proposed system are image acquisition, Gabor filtering, connected component analysis, and measurement of vein, spot, and swirl percentages.

A. System Model

The general structure of our system is shown in Fig. 2. In image acquisition phase, an image database of marble slabs was created from various marble slabs by using a regular scanner. In Gabor filtering phase, two banks of Gabor filters were created and applied to the scanned image for the detection of marble texture. In the connected component analysis phase, geometrical properties of components were used with different thresholding parameters to detect the meaningful features. In the final phase of the system, scores are assigned to differentiate and measure the percentage of veins, spots, and swirls.

Marble slab images were acquired from 40 marble slabs by using a scanner at 300 dpi with 256 gray levels. The slabs are 30cm by 30cm in size. We preferred using scanners instead of cameras due to the controlled imaging environment convenience such as lighting and positioning.

B. Gabor Filtering

Gabor filters have been widely used for texture analysis and extraction of orientation information. These filters are especially very popular to obtain information about the textural features.

The Gabor function is a complex exponential modulated by a Gaussian function in the spatial domain. It also acts as a band pass filter in the frequency domain. The Gabor function is shown by

$$H\left(x,y\right) = s\left(x,y\right)g\left(x,y\right)\ , \tag{1}$$

where *s(x,y)* is the complex sign in sinusoidal shape and *g(x,y)* is two dimensional Gaussian function.

Young *et. al.* [6] defined the general formula of 2-D Gabor filter kernel g(x,y,σ_x,σ_y,Ω_x,Ω_y) used in this system by

$$g = \frac{1}{\sqrt{2\pi}\sigma_x} e^{-\left(\frac{x^2}{2\sigma_x^2}\right)} e^{j\Omega_x x} \frac{1}{\sqrt{2\pi}\sigma_y} e^{-\left(\frac{y^2}{2\sigma_y^2}\right)} e^{j\Omega_y y}\ , \tag{2}$$

$$\Omega_x = \Omega_0 \cos\theta\ , \tag{3}$$

and

$$\Omega_y = \Omega_0 \sin\theta\ , \tag{4}$$

where space constants σ_x and σ_y define the Gaussian envelope, Ω_x and Ω_y show the frequency value, along the *x* and *y* axis. In (3) and (4) the symbol θ represents orientation value in radian base. Different Gabor filters can be constructed by the specific choices of Ω and σ at various orientations.

A constraint *k* suggested by Lee [7] is given by

$$\sigma\,\Omega = k\ . \tag{5}$$

This equation defines the inverse relationship between Ω and σ which is based on neurophysiological data for the visual cortex. In our system we have imposed the inverse relationship and chosen *k* as π. We have chosen σ as 2.0 and created Gabor filters at eight different orientations: 0, π/8,...,7π/8. Two banks of Gabor filters were created containing these eight gabor filters. The sizes of Gabor filters selected as 9x11 and 17x11.

Generally, the size of Gabor filter is chosen as *m* by *m* but for some elongated objects like veins the filter size can be adjusted to *m* by *n* where *m* is considerably larger than *n*. We used the rotation ability of Gabor filters with different orientations to capture the elongated nature of the veins. Veins differ in their widths therefore we used a second filter bank. Applying filters to the original image created two sets of eight different response images. For each of these sets, the maximum from the eight response values is selected for each pixel. At the end, we obtained a response image for each filter bank. One of these images is called narrow vein (*nvi*) which is the result of 9x11 Gabor filter bank and contains responses from the narrow veins. The other image is called wide vein (*wvi*) which contains responses for both wide veins, spots, and swirls. These two images play a significant role in finding the feature differences in veins, spots, and swirls. Fig. 3-a shows a part of a sample image. The corresponding *nvi* is shown in Fig. 3-b. The *wvi* is shown in Fig. 3-c.

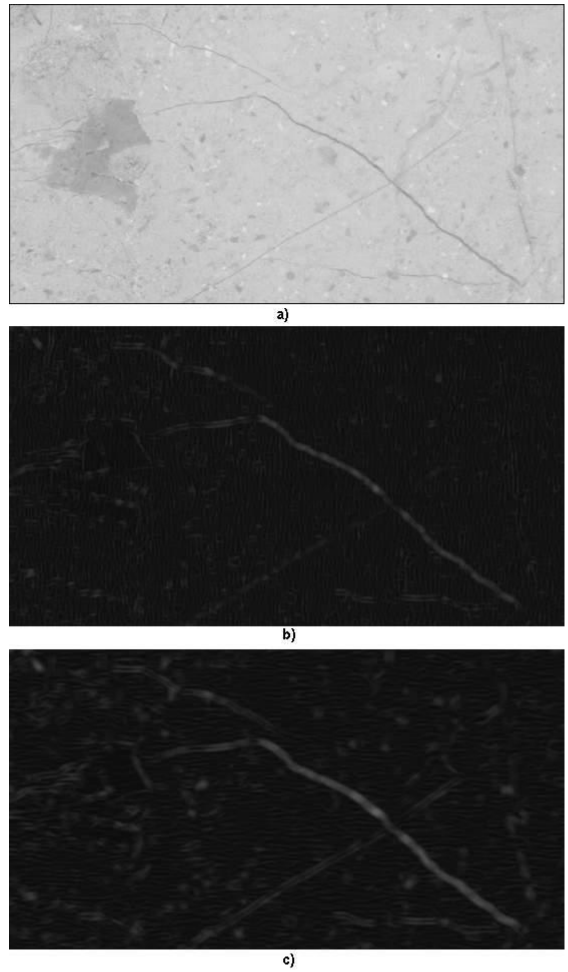

Fig. 3. A part of sample marble slab image from our database and the corresponding narrow and wide vein image: a)original image, b)corresponding narrow vein image, c)corresponding wide vein image.

C. Connected Component Analysis

Connected Component Analysis takes place after Gabor filtering phase. This phase extracts veins, spots, and swirls from Gabor filtering results by binarization of the images, tracing veins, analyzing the rest of the structure.

The connected component analysis requires the binarization of the images obtained from the previous phase. The binarization is done by selection of a threshold *bt* between 0.0 and 1.0. Selection of *bt* is important because the lower values *bt* introduces large levels of noise to the remaining processes. In contrast, higher values of *bt* eliminates useful image features. In our system, we used the value of 0.125 as *bt* and we found it to be very robust.

The proposed system analyses the binarized versions of *nvi* and *wvi* by the connected component labeling method with 8 neighbors [8]. Areas of connected components are calculated in pixel units and thresholded with a parameter, called area parameter (*ap*). Those components with areas smaller than threshold *ap* are eliminated. In all the experiments we performed, we selected *ap* as 0.1% of the total image area.

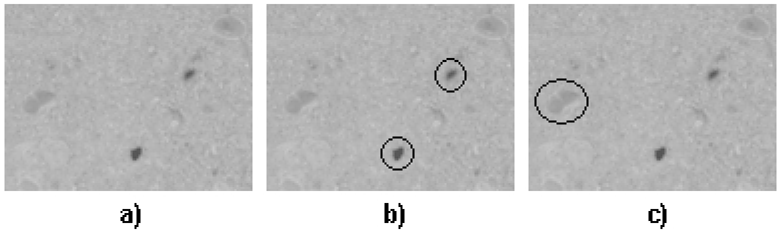

Fig. 4. A part of marble slab image from our database and corresponding areas of spots and swirls with thresholding *vgr* with *vt*=10: a)original image, b)corresponding spot areas, c)corresponding swirl areas.

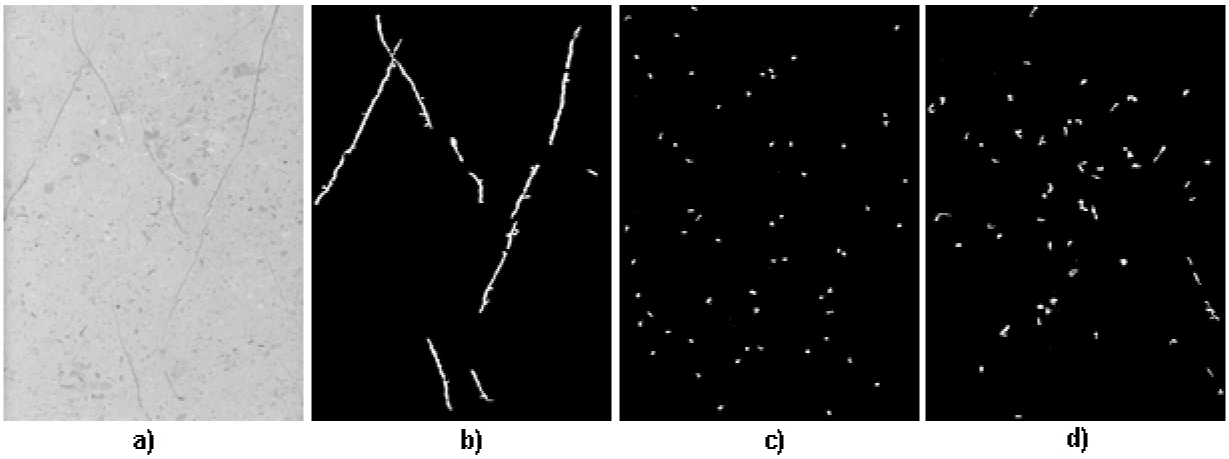

Fig. 5. A sample marble slab image from our database and the veins, spots, and swirls found at the end of connected component analysis phase: a)original image, b)veins found at the end of main step of connected component analysis, c)spots found at the end of main step of connected component analysis, d)swirls found at the end of main step of connected component analysis.

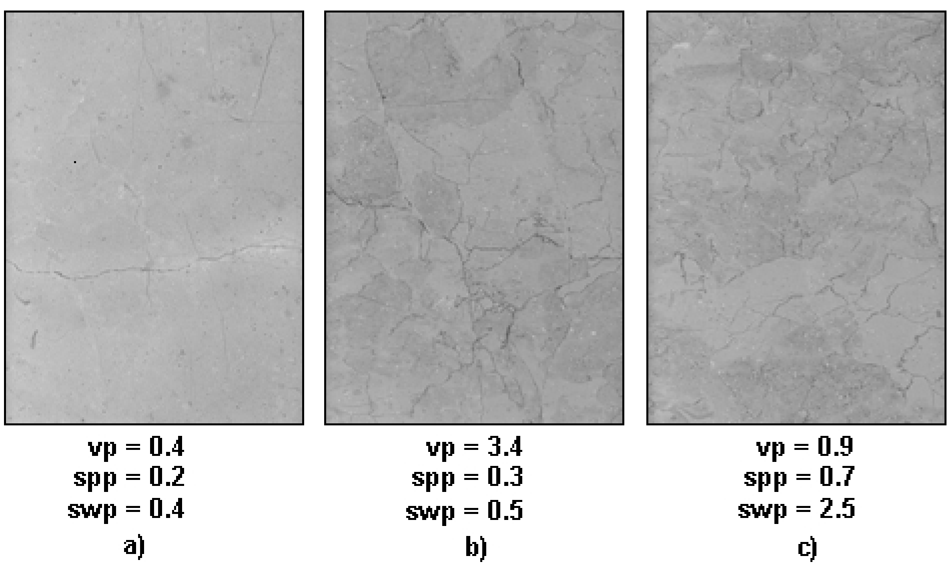

Fig. 6. The slab samples and their *vp*, *spp* and *swp* values.

After the thresholding step described above, the *nvi* contains either complete veins if they are narrow or traces of veins if they are wide. *wvi* contains information about wide veins and spots-swirls. We would like to measure the amount of veins, spots, and swirls in the marble tile image. Therefore we need to filter out the traces of veins from the *wvi*. For this purpose we take an intersection of *nvi* and *wvi*, which produces a binary image. Then we remove all the components in *wvi* that are in contact with this intersection. These removed pixels are added to *nvi* which now includes the image sections that contain the veins in the marble slab. *wvi*, on the other hand contains all the image sections that correspond to spots and swirls. At this phase, the process of connected component analysis is over but separation of spots and swirls is still needed.

The variances of Gabor filter bank responses are observed to be different for spot regions and swirl regions. In order to take advantage of this property, firstly the average of the eight response values *aer* for the 9x11 filter bank response is calculated by

$$aer \ = \ \frac{1}{8}\sum_{i=0}^{7}(Gabor\ response\ of\ \theta(i)), \tag{6}$$

for each pixel where $\theta(0)$=0, $\theta(1)$=π/8,..., $\theta(7)$=7π/8. Then the average of Gabor response value (*agrv*) for every component j is calculated by taking average of *aer* for the total pixels in this component by

$$agrv_j \ = \ \frac{1}{\#\ pixels\ in\ j}\sum_{i=first\ pixel}^{last\ pixel} aer_i. \tag{7}$$

At the end, the variance of Gabor response (*vgr*) for every component j calculated by

$$vgr_j \ = \ \frac{1}{\#\ pixels\ in\ j}\sum_{i=first\ pixel}^{last\ pixel}(aer_i - agrv_j)^2. \tag{8}$$

While spots possess higher *vgr* values, swirls possess lower *vgr* values. We employed a threshold value *vt* between 1-254 on *vgr* values the to separate spot and swirl components. Fig. 4-a shows a part of sample marble image from our database. Corresponding areas of spot components (Fig. 4-b) and areas of swirl components (Fig. 4-c) found with *vt*=10 circled on the figures. Fig. 5-a shows a sample marble image from our database. The result of connected component analysis is shown in figures 5-b, 5-c, and 5-d.

D. Measurement of Vein, Spot, and Swirl Percentages

The previous phases produce three binary images. One of these images contains the veins, the other contains spots, and the last one contains swirls. The percentage of veins (*vp*) contained in the marble slab can be calculated by simply taking the ratio of vein pixels over the total pixels in *nvi*. The same procedure can be applied to *wvi* to produce the percentage of spots (*spp*) and swirls (*swp*) in the marble slab using the formulas

$$vp = \frac{\#\ of\ vein\ pixels}{total\ pixels} \ \times\ 100\ , \tag{9}$$

$$spp = \frac{\#\ of\ spot\ pixels}{total\ pixels} \ \times\ 100\ , \tag{10}$$

and

$$swp = \frac{\#\ of\ swirl\ pixels}{total\ pixels} \ \times\ 100\ . \tag{11}$$

The numbers *vp*, *spp*, and *swp* are the main results obtained by our system which indicate the percentage of veins (*vp*), the percentage of spots (*spp*), and the percentage of swirls (*swp*) contained in the marble slab image. Using these three values, any machine learning method such as decision trees or neural networks can be trained for classification. In addition, they could be used with simple threshold intervals in three dimensions. If such a classifier is used, it would be highly customizable by the end user because the threshold intervals can be intuitively modified or new threshold intervals can be added to the system for new classes.

We have calculated *vp*, *spp*, and *swp* values for all the images in our database by using our system. Fig. 6 shows three representative examples with *vp*, *spp* and *swp* values which visually show the accuracy of our system. We obtained very similar results with all the images that we tested in our database.

Note that our extracted features are much more intuitive than the features used in literature. For example, [3], [5] uses SDH features of contrast, mean, entropy, correlation, etc. to assign each marble image to a quality class. These features cannot be used by an end user to intuitively decide the quality or texture class of the marble image. Thefore, the systems in the literature had to employ a classifier with a trainining phase, which makes the infield customization of these systems inpractical. The extracted features of our system, on the other hand, represent meaningful numbers about the marble texture. For example, an end user might determine threshold intervals for a marble class with high amount of veins without any difficulty. However, doing the same thing with features from the literature is not always possible.

III. Experimental Results

As we mentioned in the Sec I, verification of classification systems is very difficult when the classes are determined by human visual inspection. The human experts usually make different decisions on the same data which eliminates the possibility of a sound ground-truth data. In order to verify our system without any ground-truth data, we asked four different human experts to sort marble slabs with respect to the percentage of veins, spots, and swirls. As expected, the final sortings of the human experts were slightly different. We call this difference, inter-expert variation. We argue that any practical marble slab classification system should sort the same slab set in the same inter-expert variation. The inter-expert variation numbers between two expert sortings are calculated by taking the positional difference of the same marble slab in the two sorted sequence. For every slab the absolute sequence difference is calculated as the variation value (*vval*) between the sequences. The average variation value for veins, spots or swirls per marble slab is calculated by

$$avg.\ var.\ value\ per\ marble \ = \frac{\sum_{i=1}^{\#\ of\ marble\ slabs} vval_i}{\#\ of\ marble\ slabs}\ . \tag{12}$$

The normalized average variation value (*navv*) percent for vein, spot, and swirl is calculated by

$$navv\% \ = \frac{avg.\ var.\ value\ per\ marble}{\#\ of\ marble\ slabs} \ \times\ 100\ . \tag{13}$$

TABLE I

EXPERIMENTAL RESULTS FOR NORMALIZED AVERAGE VARIATION VALUES, MEANS AND STANDARD DEVIATIONS FOR VEINS.

X	Human.Exp.1	Human.Exp.2	Human.Exp.3	Human.Exp.4	Mean	Std.Dev.
SYSTEM.	3.4	6.1	7.1	4.5	5.3	1.6
Human.Exp.1	-	6.9	7.7	6.4	7.0	0.7
Human.Exp.2	6.9	-	8.8	5.4	7.0	1.7
Human.Exp.3	6.4	5.4	-	8.0	6.6	1.3
Human.Exp.4	10.5	13.5	15.1	-	13.0	2.3

TABLE II

EXPERIMENTAL RESULTS FOR NORMALIZED AVERAGE VARIATION VALUES, MEANS AND STANDARD DEVIATIONS FOR SPOTS.

X	Human.Exp.1	Human.Exp.2	Human.Exp.3	Human.Exp.4	Mean	Std.Dev.
SYSTEM.	5.1	5.2	5.7	7.1	5.8	0.9
Human.Exp.1	-	4.5	5.4	7.3	5.7	1.4
Human.Exp.2	4.5	-	5.8	7.2	5.8	1.3
Human.Exp.3	5.4	5.8	-	8.8	6.7	1.9
Human.Exp.4	7.3	7.2	8.8	-	7.8	0.9

TABLE III

EXPERIMENTAL RESULTS FOR NORMALIZED AVERAGE VARIATION VALUES, MEANS AND STANDARD DEVIATIONS FOR SWIRLS.

X	Human.Exp.1	Human.Exp.2	Human.Exp.3	Human.Exp.4	Mean	Std.Dev.
SYSTEM.	9.2	9.8	8.3	7.6	8.7	1.0
Human.Exp.1	-	9.9	8.1	8.8	8.9	0.9
Human.Exp.2	9.9	-	11.2	7.4	9.5	1.9
Human.Exp.3	8.1	11.2	-	6.4	8.5	2.4
Human.Exp.4	8.8	7.4	6.4	-	7.5	1.2

Table I, Table II, and Table III shows the calculated normalized average variation values, means and standard deviations for veins, spots, and swirls respectively. The normalized average variation values between humans and the system are not included for the calculations of mean and standard deviations of the experts.

The analysis of the results shown by Table I, Table II, and Table III indicates a considerable inter-expert variation. We also observe that our system shows differences when compared to human experts. However, the variation between our system and human experts are very similar to inter-expert variation. Therefore, we can confidently replace one of the human experts with our system and the final classification results would not be expected to change. Note that the employment of inter-expert variation values is a much tougher method than the inner-class and within-class analysis as done by Martinez-Alajarin *et. al.* [5]. Firstly, our method realizes the fact that there is no reliable ground truth data. Secondly, our method does not assume a small number of classes that might increase the possibility of accidental assigments to the correct classes. Finally, testing the system directly on *vp*, *spp*, and *swp* values would be the ultimate verification method.

IV. CONCLUSION

Marble tile business is a large and fast growing industry both at global and national markets. Classifications of marble tiles by computers would be beneficial in terms of production costs, quality control, and better throughput. We presented a marble tile feature extraction system which can be easily used for any classification. Employment of the Gabor filter makes it possible to differentiate between different texture types and the system can assign scores for each tile in terms of texture features which makes our system very portable to different classification system. The final numerical results obtained from the system are very intuitive and they can be used to customize the classification process by the end user. Customizability is a crucial feature for any practical marble classification system because the classification rules may change due to the orders from customers.

We also presented a novel verification system that addresses the problem of lack of reliable ground-truth data. We argue that any practical automated classification system should satisfy the inter-expert variability numbers. The experiments performed on 40 marble tiles show that our system can be used reliably in real life marble classification.

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