An automated industrial conveyor belt system using image processing and hierarchical clustering for classifying marble slabs

M. Alper Selver a,*, Olcay Akay a, Fikret Alim b, Sibel Bardakçıl c, Mehmet Ölmez d

a Dokuz Eylul University, Department of Electrical and Electronics Engineering, 35160 Buca / Izmir, Turkey
b Arçelik A.S., Cumhuriyet Mah., E-5 Yen Yolu, No. 1, 34520 Beylikdüzü / Istanbul, Turkey
c SBM Teknoloji Ürünleri Satis ve Pazarlama A.Ş., Kemalpaşa Yolu, 3 km, Kemalpaşa / Izmir, Turkey
d Dokuz Eylül University, İzmir Vocational School, Buca / Izmir, Turkey

ARTICLE INFO

Article history:
Received 20 November 2008
Received in revised form
17 June 2010
Accepted 14 July 2010

Keywords:
Marble classification
Clustering
PLC control
Automated conveyor belt system

ABSTRACT

Although there are many industrial machines used in marble industry, classification of marble slabs in terms of quality is generally performed by human experts. Due to economic losses of this rather subjective process, automatic and computerized methods are needed in order to obtain reproducible and objective results in classification. With the aim of remediying this insufficiency in marble industry, a new electro-mechanical system, which automatically classifies marble slabs while they are on a conveyor belt and groups them with the help of a control mechanism, is proposed. The developed system is composed of two parts: the software part acquires digital images of marble slabs, extracts several features using these images, and finally performs the classification using clustering methods. The hardware part is composed of a conveyor belt, a serial port communication system, pneumatic pistons, a programmable logic controller (PLC), and its control circuits, all employed together for grouping the marble slabs mechanically. Although similar studies exist, this paper proposes three novelties over the existing systems. Firstly, a new hierarchical clustering approach is introduced for quality classification without requiring a training set. Secondly, a new feature set based on morphological properties of marble surface images is proposed. Finally, an electro-mechanical system is designed for accomplishing the task of sorting out the classified marble slabs. In the literature, only a system with a labeling mechanism has been presented. Our system, on the other hand, comes with a complete conveyor belt acting as an element that links the production line with the proposed system. This allows the possibility of embedding the proposed system into the production line of a marble factory. It has been observed that although the performance of the developed system is not as high as neural network based systems that use training, it could still be employed in industry when there is no available training set of samples. With this advantage, it provides an increase in the quality control standards of marble slab classification, since marbles are classified with an objective and uniform-through-time criterion.

© 2010 Elsevier Ltd. All rights reserved.

1. Introduction

Thanks to the recent developments in data acquisition, processing, and process control systems, efficiency of many of the industrial applications (i.e. automobile, electronics, rock, and metal industries) has been improved with the help of automated visual processing and classification systems [1]. Technological advances in digital image acquisition [2,3] and processing [4] have allowed building automated visual inspection (AVI) systems [5–7]. Feasibility studies [8] and different applications of AVI systems are presented in the literature for classification of several products/materials of industrial value [6–11].

As for moving conveyor belts, design and implementation of such a system is very challenging and consists of several difficulties, [12,13], which necessitate employing different approaches for overcoming these problems [14]. In quality classification tasks, the classification output determines the category, or quality group, of a particular item. A typical classification process comprises five main steps:

(i) Locating or recognizing the items on the conveyor belt via some type of a sensor such as a camera, scanner, etc.
(ii) Acquiring the necessary data from the item (i.e. taking pictures, measuring the amount of reflected light,
electromagnetic wave, or another type of signal). The acquisition device is usually located above the conveyor belt to view the items orthographically.

(iii) Processing the data to extract several useful features.
(iv) Classification of the item using the extracted features and a classifier.
(v) Performing the necessary action following the classification result of the classifier.

Marble quality classification is based on some physical, mechanical, and technological properties required by universal standards [15]. At the same time, the classified marble slabs should reflect attractive color and pattern choices. Important constraints for aesthetic appearance are homogeneity, texture, color, distribution of limestone (beige colored regions in Fig. 1), cohesive material (red–brown colored regions in Fig. 1), and thin joints filled by cohesive material (red–brown colored veins in Fig. 1). Thus, two marble slabs, one containing unified cohesive material regions (Fig. 1(c)) and the other containing vein-like cohesive material structures (Fig. 1(b)), should be treated as belonging to different quality groups even if they have the same amount of cohesive material.

Since false classification of marbles can result in major economic losses, it is necessary to classify marble slabs correctly according to their quality and appearance. The classification process is mostly carried out at the end of a production line, where human experts evaluate and classify the products visually according to the parameters mentioned above. However, using human experts for classification can be error-prone owing to subjective criteria of the operator (even different operators due to shift work) and the visual fatigue after a period of time, which degrades the classification performance. Thus, it is necessary to use an automated system capable of performing the same classification tasks that are currently carried out by human experts.

Several different feature extraction methods (i.e. sum and difference histograms, statistical texture based features, wavelets, etc.) and classifiers (i.e. clustering methods such as K-Means, fuzzy C-Means, or neural networks such as multi-layer perceptron and support vector machines with various distance measures) have been employed for quality classification of marble slabs [16–21], but only the method in [21] is implemented in an industrial facility. Although the results were successful in [21], the data set was not quite diverse (i.e. extra, commercial, and low

![Fig. 1. Typical marble slab images from four different quality groups: (a) Group 1, (b) Group 2, (c) Group 3, and (d) Group 4.](image-url)
quality groups) and the number of images used in the study was not large enough (i.e. 75 samples only). It has been shown in [22] that the application of the previously mentioned methods to a diverse and large data set cannot provide as successful results as reported for smaller data sets with less diversity. Moreover, it is also shown that the performance of a system would be limited if color-based, textural, or spectral information are used separately for classification. To overcome this limitation, in [22], these feature sets (i.e. pixel intensity, textural, and spectral) have been combined in a cascaded manner with a hierarchical classification strategy. By doing so, different feature sets, which represent different sub-group(s) in a quality group, are extracted in a successive manner, so that each feature set is used only for the sub-group(s) that can be correctly classified by that feature set.

Although, artificial neural network (ANN) classifiers can achieve very high classification rates [21,22], a training set is needed for adjusting the weights of an ANN. This data set should contain enough number of samples and represent as much variations as possible for an effective learning. However, when a new natural stone is to be classified in an industrial facility such a large number of samples might not be available for training. Clustering methods can be employed in such situations since they do not require any training set. So far, clustering has been used for vein determination only [23–25], supplying yet another feature for an ensuing classification task. However, clustering itself can also be employed for classification. In this work, the strategy in [22] is modified to include clustering algorithms (instead of ANN classifiers) in implementing a hierarchical approach for clustering based classification that can be used in the absence of a training set.

To increase the success rate of the newly proposed clustering based technique, a new feature set is also introduced. This feature set contains a number of morphological features that are especially useful for differentiating unified vs. vein-like cohesive material regions on marble slabs.

We also spent considerable time and effort for developing and building the hardware part of our system. The system in [21] consists of image acquisition, processing, and slab labeling operations installed on an existing conveyor belt without any process control. In order to achieve full control over the process of marble classification, in this paper, we also introduce our newly built electro-mechanical system that can be added to the end of a production line.

The block diagram of our complete system is shown in Fig. 2. As the marble slabs are moved on a conveyor belt, the proposed system automatically classifies them by extracting features using different image processing techniques, and then, by labeling slabs using either neural networks or clustering methods. The process is then finalized by grouping the marble slabs with a control mechanism.

The proposed system is composed of two main parts: the software part involves image acquisition, image processing, clustering based classification methods, and serial port communication systems. The processing steps performed in the software part are as follows: image acquisition through MATLAB using a web-cam having a CCD sensor, correction for non-uniform illumination, application of a thresholding algorithm for segmentation, feature extraction, quality classification, and finally, a serial port callback that can be thought as an interrupt in MATLAB.

The hardware part of the system includes a conveyor belt, pneumatic pistons, and their control mechanisms for grouping the marbles mechanically. The hardware part also includes a programmable logic controller (PLC) as the main controller and an auxiliary microcontroller as the communication tool between the PLC and MATLAB. The system involves infrared sensors that

![Fig. 2. Block diagram of the electro-mechanical conveyor belt system for marble classification.](image-url)
are required for position control, capturing images, and getting feedback on the operation of the system. The system and its behavior can be controlled and observed using the Supervisory Control and Data Acquisition (SCADA) software and light emitting diodes (LED). Thus, the conveyor belt acts as an element that links the production line with the automatic classification system, in case the system is to be embedded in the production line of a marble factory. It has been observed that the developed system could effectively be employed in the industry, considering its short processing and classification time. It also provides an increase in quality control standards of marble slab classification process by allowing the classification to be carried out with an objective and uniform-through-time criterion.

The rest of the manuscript is organized as follows: Section 2 describes the data set used in this study. Section 3 explains the image acquisition, processing, and classification steps of the proposed system. In Section 4, details of the PLC and the conveyor belt system are outlined. Finally, Section 5 includes results and discussions.

2. Marble data set

The marble specimens used in this study are extracted from a mine in Manisa region of Turkey. Although there are not unique criteria for classifying marble specimens, color scheme, homogeneity, size, orientation, thickness, and distribution of the filled joints (red–brown colored veins) are often used to visually perform the classification by human experts. Similarly, classification of marble slabs in our study is performed by human experts, considering the smooth gradients of color, the presence of joints on the surface, the continuity, thickness, and orientation of joints (represented with the term “veins”), and the ratio of limestone grains and the cohesive matrix. Under these criteria, four quality groups have been considered:

1. homogenous limestone (beige color) (Fig. 1(a));
2. limestone with filled thin joints (veins) (Fig. 1(b));
3. brecciated limestone (composed of limestone grains of different shape and size cemented with cohesive matrix) (Fig. 1(c)). Here, cohesive matrix is defined as the collection of joints (veins) that are unified to construct a larger area of material; and
4. homogenous cohesive matrix (Fig. 1(d)).

3. Marble classification system

3.1. Image acquisition and pre-processing

Image processing starts with acquiring the digital image. The quality of the captured images, illumination conditions, and the resolution of the digital images should be high enough to reach a satisfactory success rate. However, as resolution and quality of the acquired images increase, the processing times also increase. This is critical since the designed system is desired to work online. The image acquisition part of the system is designed in order to standardize capturing of the marble surface images. The system consists of a camera (an 8 megapixel Canon EOS 350D digital camera with 18–55 mm EF-S zoom lens or a CCD web-cam), connection cables, light sources, a desktop computer, and a cabinet housing all these parts. The complete image acquisition system is shown in Fig. 3.

The 8 megapixel camera produces high quality images with a resolution of 1575 × 1550. Although, the resolution of images is high enough to provide necessary information, transferring images to the computer and displaying them in MATLAB require more than 20 s, which is much more than tolerable for an online system. Our experiments showed that using a resolution of 315 × 310 was enough to process images without affecting the success rate. For this purpose, a CCD web-cam was used. The camera was set to have a position perpendicular to the bottom surface of the cabinet and the USB connection to the desktop personal computer was established via cables.

The cabinet was used to ensure a fully isolated and uniformly illuminated area. The fluorescent light sources were positioned to prevent blazing as much as possible that may occur at the surface of marble samples. Thus, in the proposed system, fluorescent lamps suitably positioned in the closed and black painted cabinet are used for illumination. Although the light sources inside the cabinet are located carefully so that illumination can be made uniform inside the image acquisition unit, some non-uniform illumination remained. To compensate for the remaining non-uniformity, image of a white paper is captured and then the maximum gray-level intensity value in the green channel of this image is calculated. (The green channel is selected after several experiments on conversion of the RGB image to grayscale.) Then, a difference image is obtained by subtracting all gray-level intensity values from the maximum value calculated using the image of the white paper. This difference image is added to the captured marble slab images in order to correct for the effect of non-uniform illumination. The final image obtained after correction of non-uniform illumination and the cropping operations is shown in Fig. 4. As the last step of the pre-processing operations, a 3 × 3 median filter is applied to smooth the effect of small regions having significantly different gray-level values from their neighboring pixels.

Next, the histogram of the resulting image is calculated. Since the obtained histogram is known to be bimodal, an optimum threshold value is determined by finding the pixel value having the minimum gray-level intensity that corresponds to a local minimum in a pre-determined interval where the threshold value should be. This value is applied to the image and a binary image is obtained. In the binary image, white regions correspond to the red–brown colored cohesive material in the original image and black pixels represent the beige-colored limestone in the original marble image. The connected components of the red–brown
colored cohesive material regions in the binary image are labeled in order to be able to use them in the feature extraction step.

The numbers of samples for each quality group (from 1 to 4) are 172, 388, 411, and 187, respectively, comprising a data set of 1158 samples in total.

3.2. Image processing operations and extraction of features

Textural features, which are extracted using sum and difference histograms (SDH) [26] and used for computing features of mean, variance, energy, correlation, entropy, contrast, and homogeneity, have been employed in the literature [21] for marble classification. On the other hand, wavelet transform based features [16] aim to obtain the energy level of a sample and check if it is inside a band of frequency and then calculate mean, median, and variance of each level of decomposition. In [22], it is shown that textural features or wavelet features are not enough for representing a diverse data set. The reason behind this can be explained as follows.

Physical and mechanical properties and durability of marble specimens can change due to the amount, distribution, and shape of cohesive material (i.e. red–brown colored regions). For instance, joints filled with cohesive material reduce the compressive strength of the marble. Thus, two marble slabs, one with unified cohesive material parts (Fig. 1(c)) and the other containing vein-like cohesive material structures (Fig. 1(b)), should be treated as belonging to different quality groups even if they have the same amount of cohesive material. Thus, to differentiate these groups, morphological features are employed by taking advantage of their representation capabilities on determining shapes and their areas. Accordingly, several experiments have been carried out to come up with a feature set that can effectively represent the characteristics of veins and cohesive material regions on marble slab surfaces. In [22], a set of morphological features (i.e. area, compactness, and elongatedness) has been introduced for characterization of veins. Although these features are well enough to bring the success rate of an ANN classifier into a higher performance level, simulations show that a more informative feature set is required to differentiate veins and cohesive material regions when clustering methods are used. Thus, in this study, the morphological feature set is extended to include area, perimeter, compactness, elongatedness, rectangularity, and eccentricity.

The strategy behind the determination of the features is based on their representation capability of marble slabs that have similar textures even though they belong to different groups. These similar samples reside especially in Groups 2 and 3. Samples in Group 2 consist of limestone regions having filled thin joints (veins) (Fig. 1(b)) while samples in Group 3 have joints (veins) that are unified to construct larger areas of cohesive material (Fig. 1(c)). When unified joints are not large enough, classification problems may occur. Therefore, morphological features are calculated for the red–brown colored cohesive material regions that are labeled in the pre-processing stage. To demonstrate the effectiveness of morphological features, especially in discriminating the marble slabs of Groups 2 and 3, synthetic images representing our quality groups are generated and morphological features of these synthetic images are extracted. For instance, Fig. 5(b) and (c) represent samples of Groups 2 and 3, respectively. Samples belonging to these two quality groups have approximately the same amount of cohesive material regions but in different forms and shapes. In Table 1, values of the morphological features for the synthetic images in Fig. 5 are given.

It can be observed from Table 1 that perimeter, rectangularity, elongatedness, compactness, and eccentricity produce significantly different values, notably for Groups 2 and 3, increasing the possibility of separation of samples belonging to these two groups in the feature space.

Features forming the morphological feature vector are summarized below, together with some of their values for some critical samples of Groups 2 and 3 that are hard to differentiate.
A feature this is defined as the sum of areas surrounded by the outer contours of all (i.e., \( L \)) labeled regions divided by the image size, which is calculated by multiplying the image width with the image height, and equals to 97,650 (315 × 310);

\[
\text{Area} = \frac{A_1 + A_2 + \cdots + A_l}{\text{image size}}
\]  

(1)

**Perimeter.** Perimeter is the distance around the boundary of a labeled region. It is calculated using a binary image containing only the perimeter pixels of labeled regions in the input image. A pixel is part of the perimeter if it is nonzero and it is connected to at least one zero-valued pixel when four-connectivity is used to determine connection. The distance between each adjoining pair of pixels around the border of the labeled region is calculated to obtain the perimeter value.

**Compactness.** Compactness, referring to [5], is a very useful shape descriptor to evaluate the complexity of contours. Compactness is independent of translation, rotation, and scaling. The most compact region that possesses the minimal value of compactness is a circle whose compactness is equal to 4\( \pi \), which is approximately 12.56. Compactness is defined as

\[
\text{Compactness} = \frac{\text{number of pixels in labeled region}}{(\text{labeled region border length})^2}
\]

(2)

In our data set, marble sample images that belong to Group 2 have less compact labeled regions than samples from Group 3. This is because the cohesive material regions of Group 2 are in the form of veins that are thin structures. However, samples of Group 3 have larger veins that are unified forming more compact cohesive material regions. For instance, the average value of compactness for a typical sample in Group 2 is 102.72 while it is 36.14 for a typical sample from Group 3. For our synthetic images in Fig. 5(b) and (c), compactness is calculated as 104.99 and 49.09, respectively.

**Elongatedness.** Elongatedness, referring to [5], is computed using the width, \( l_1 \), and height, \( l_2 \), of the bounding rectangle of a labeled region and is defined as follows:

\[
\text{Elongatedness} = 1 - \frac{l_1}{l_2} \quad \text{with} \quad l_1 < l_2.
\]

(3)

The marble sample images belonging to Group 2 are more elongated than samples from Group 3, because the difference between \( l_1 \) and \( l_2 \) is higher in vein-like structures as in the labeled regions of the samples in Group 2. However, \( l_1 \) and \( l_2 \) are almost equal in the labeled regions of the samples belonging to Group 3. For example, the average values of elongatedness for two critical samples from Groups 2 and 3 are 0.76 and 0.5, respectively.

**Rectangularity.** Rectangularity is the ratio of the value of the “Area” feature over the area of the bounding rectangle defined in (3). As the labeled region becomes more rectangular (i.e. vein like cohesive material regions), the value of rectangularity approaches 1.

**Eccentricity.** Eccentricity is the ratio of lengths of major and minor axes of an object. The major axis length (in pixels) is defined as the major axis of the ellipse that has the same normalized second central moment as the labeled region. Similarly, the minor axis length (in pixels) is the minor axis of the ellipse that has the same normalized second central moment as the labeled region. The value of eccentricity is between 0 and 1.

<table>
<thead>
<tr>
<th>Group</th>
<th>Area</th>
<th>Perimeter</th>
<th>Compactness</th>
<th>Elongatedness</th>
<th>Rectangularity</th>
<th>Eccentricity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>125</td>
<td>81.65</td>
<td>53.33</td>
<td>0.050</td>
<td>0.800</td>
<td>0.311</td>
</tr>
<tr>
<td>Group 2</td>
<td>2629</td>
<td>525.39</td>
<td>104.99</td>
<td>0.944</td>
<td>0.748</td>
<td>0.998</td>
</tr>
<tr>
<td>Group 3</td>
<td>3988</td>
<td>389.36</td>
<td>49.09</td>
<td>0.149</td>
<td>0.514</td>
<td>0.520</td>
</tr>
<tr>
<td>Group 4</td>
<td>39875</td>
<td>878.42</td>
<td>19.35</td>
<td>0.017</td>
<td>0.845</td>
<td>0.174</td>
</tr>
</tbody>
</table>

3.3. Classification via neural networks

In the simplest and most straightforward methodology, the aforementioned features are used for training an ANN as a composite feature vector. Using these features, the ANN is trained and its outputs are saved in order to use them during online classification. To provide numerical balance among features, usually all features are normalized (i.e. for each feature, all values are divided by the maximum value) into the range of [0,1] before they are given to an ANN as input. After training, the feature vector for one marble slab is extracted and the resulting feature vector is applied to the ANN. The network decides on the quality group of the marble slab based on these features.

However, this traditional approach can be further improved using different techniques. As discussed in detail in [22], application of the above mentioned classification strategy to a diverse and large data set could not provide as successful results as reported for smaller data sets with less diversity. Moreover, it is also shown that the performance of a system would be limited if color-based, textural, or spectral information are used separately for classification. To improve upon this limitation, in [22], these feature sets (i.e. color-based, textural, and spectral) have been combined in a cascaded manner with a hierarchical classification strategy. By doing so, different feature sets, which represent different sub-group(s) in a quality group, are extracted in a successive manner, so that each feature set is used only for the sub-group(s) that can be correctly classified by that feature set. The simulation results in [22] clearly demonstrate that the proposed hierarchical scheme improves the classification performance.

3.4. Classification via clustering

Although ANN methods can achieve considerably higher correct classification rates than clustering methods, they require a training set that should be both large enough (i.e. a high number of samples) for effective learning and diverse enough to be able to represent all possible variations within the data set. This might not be possible in real life since production lines often need to process different kinds of stones in a short period of time. In that case, clustering methods can be a good alternative to ANN classifiers. Therefore, in this paper, the hierarchical strategy in [22] is borrowed and used with clustering algorithms (instead of ANN classifiers). The important issue of initialization (i.e. cluster center determination) is handled using typical members of the quality groups.
Although, there are studies [23–25] focusing on applications of different clustering techniques for marble classification, these studies are mainly concerned with vein classification on a marble slab rather than classification of marble slabs into different quality groups. Thus, the issue of having a classifier that can work on very limited or no training has not yet been investigated. In this paper, different clustering strategies involving K-Means algorithm are used and tested for quality classification of marble slabs. Moreover, a hierarchical clustering approach has been implemented in a similar manner to [22].

Hierarchical clustering [27] creates a hierarchy of clusters that can be represented in a tree structure where the root of the tree consists of a single cluster containing all observations and the leaves correspond to individual observations. Algorithms for hierarchical clustering are either agglomerative, in which one starts at the leaves and successively merges clusters together, or divisive, in which one starts at the root and recursively splits the clusters. The choice of which clusters to merge or split is determined by a linkage criterion, which is a function of the pairwise distances between observations. On the other hand, our approach, as illustrated in Fig. 6, is based on using each feature space as one level of clustering hierarchy and adjusting the parameters to achieve the best performance in the end when the results of all levels are merged together. Thus, different feature sets are used in a cascaded manner. At each clustering level, some of the input data, which are determined based on an error criterion, are not clustered (Fig. 7(a)). These un-clustered data become input to the next clustering level that runs in a different feature space (Fig. 7(b)). In our study, each clustering step (level) consists of a fixed number (i.e. four) of clusters corresponding to four quality groups. At the end, union of the clusters belonging to the same quality group is formed to construct the overall quality group.

One of the most crucial issues in designing clusters is determination of their centers and radii, both of which can be defined over different range of values. If a single clustering level was used, the radii of clusters would automatically become large enough so that all samples could be clustered. However, in our hierarchical clustering algorithm, the radii of the clusters are limited to a value satisfying a predefined margin from the closest cluster center. A second constraint, which requires the cluster radius to be equal to the minimum center-to-center distance among clusters of a level, is also added. This constraint prevents any of the cluster radii from being very large even if its center is significantly far from the centers of other clusters. As a natural result of these radius restrictions, some samples are not clustered as mentioned above (Fig. 7). These samples are the ones that are farther away from all cluster centers as compared to the calculated radii values for the clusters of that level. Simulations show that these un-clustered samples correspond to the ones that

![Fig. 6. Hierarchical clustering scheme. N is the number of quality groups and K is the level index. At the end of the tree, each quality group is constructed by merging its corresponding clusters at each level using union, \( \cup \), operation.](image-url)
are harder to be clustered correctly using the feature set of that level. Thus, it is better to cluster them at another level where they are closer to a cluster center.

3.5. Simulation results for clustering

As introduced in Section 1, several different features have been extracted to represent the characteristics of marble slabs. Among them, texture based features [21] and wavelet features [16] have displayed important success rates. Thus, these features have been applied to our data set for comparison with our proposed hierarchical method.

In [21], textural features are extracted using SDH [26] with the distance metric chosen as the 8-neighborhood. Using the obtained SDH vectors, seven statistical features (mean, variance, energy, correlation, entropy, contrast, and homogeneity) [21] are computed. For each color channel, these calculations produce a total of 21 features (7 features × 3 color channels). On the other hand, in [16], the aim is to obtain the energy level of a sample and check if it is inside a band of frequency or not. Discrete wavelet transform (DWT) [28] is used to obtain the frequency bands, amounting to application of a series of low and high pass filtering of the original signal followed by downsampling. For the surface images of marble slabs used in this study, high pass filtering includes filtering in the horizontal, vertical, and diagonal directions. Thus, one low pass and three high pass (horizontal, vertical, and diagonal) images are generated at each level of decomposition. In our study, three levels of DWT decomposition are performed for each sample image using biorthogonal wavelets [28]. Mean, median, and variance of each level of decomposition are computed to obtain a 1 × 36 feature vector for each sample.

The six morphological features (i.e. area, perimeter, compactness, elongatedness, eccentricity, and rectangularity) used in the clustering method are extracted for each color channel and a feature vector of dimension 1 × 18 is constructed for each sample.

The clustering method used throughout this study is the K-Means method due to its simplicity in determining cluster centers and radii. However, different clustering methods can also be applied in the same manner. K-Means algorithm [27] partitions the samples in a feature space into N clusters (for our application, N is equal to 4, corresponding to the four quality groups) using an iterative procedure. The aim is to minimize the sum, J, of the distances between sample values and cluster centers over all clusters:

\[
J = \sum_{j=1}^{N} \sum_{x_i \in C_j} |x_i - \mu_j|^2.
\]

Here, \(|x_i - \mu_j|^2\) is a chosen distance measure between a sample \(x_i\), which is assigned to cluster \(C_j\) (i.e. a quality group), and the cluster center \(\mu_j\) in that feature space, providing an indication of the distances of the data points from their respective cluster centers. We first used the Euclidean distance metric and did not apply any update method [29]. Thus, there was no iteration consisting of reassigning new samples to their nearest cluster centers, followed by recalculation of cluster centers. Instead, at each level of clustering, features extracted using typical samples of each quality group have been used to determine cluster centers. As an alternative, we also employed an online update method [29], in which a cluster center is recalculated each time a new sample is assigned to the corresponding quality group.

Performance results presented in Table 2 reveal some important points. When the feature sets are used individually as the inputs of the K-Means clustering algorithm, they provide very similar correct classification rates on average (approximately 76%). However, values of correct classification rates among different quality groups greatly vary for these feature sets. For instance, when SDH and wavelet features are used, there are some notable discrepancies in the correct classification rates (CCR) of Groups 1 and 4 and the CCRs of Groups 2 and 3. Thus, we can conclude that SDH and wavelets are more successful in classifying Groups 1 and 4 compared to morphological features. In other words, there is a significant advantage of using morphological features for classifying Groups 2 and 3, just as SDH and wavelets are better suited to Groups 1 and 4. To take advantage of all feature sets, a composite feature vector can be constructed by lumping all the features together. Although classification performance increases (Table 2, last column), this method cannot exploit all advantages of different feature sets since lumping all these features together brings about a large and inevitably complex feature space.

Considering the results and discussions above, since each feature set provides some advantages on representing a different subgroup of the entire data set, cascaded use of the extracted features is performed in a way that each feature set is used for classifying the group of samples which are best represented (discriminated) by that feature space. For implementing this idea, a hierarchical clustering structure is designed in which different feature sets are used sequentially. At the first level of the hierarchy, a feature set is employed and then clustering is applied using a parameter set that enables classification of the group that is discriminated better in that feature space. At the second level, only the un-clustered samples carried over from the previous
Table 3  Correct classification rate (CCR) performance of K-Means clustering method using SDH, wavelet, and morphological features individually and altogether.

<table>
<thead>
<tr>
<th>Quality groups</th>
<th>SDH CCR</th>
<th>Wavelet CCR</th>
<th>Morphological CCR</th>
<th>Composite feature CCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>82.41</td>
<td>78.92</td>
<td>81.12</td>
<td>83.44</td>
</tr>
<tr>
<td>G2</td>
<td>75.50</td>
<td>75.08</td>
<td>74.53</td>
<td>76.17</td>
</tr>
<tr>
<td>G3</td>
<td>69.22</td>
<td>74.71</td>
<td>71.46</td>
<td>75.68</td>
</tr>
<tr>
<td>G4</td>
<td>80.13</td>
<td>78.15</td>
<td>80.44</td>
<td>81.20</td>
</tr>
<tr>
<td>Average</td>
<td>76.07</td>
<td>76.88</td>
<td>76.72</td>
<td>79.12</td>
</tr>
</tbody>
</table>

Table 2  Correct classification rate (CCR) performance of K-Means clustering method using different two- and three-level hierarchical clustering strategies (L: level).

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>84.24</td>
<td>83.17</td>
<td>82.50</td>
<td>85.41</td>
</tr>
<tr>
<td>G2</td>
<td>76.07</td>
<td>78.16</td>
<td>79.01</td>
<td>81.26</td>
</tr>
<tr>
<td>G3</td>
<td>72.85</td>
<td>76.43</td>
<td>77.38</td>
<td>82.13</td>
</tr>
<tr>
<td>G4</td>
<td>83.62</td>
<td>81.82</td>
<td>82.04</td>
<td>85.63</td>
</tr>
<tr>
<td>Average</td>
<td>79.20</td>
<td>79.90</td>
<td>80.23</td>
<td>83.60</td>
</tr>
</tbody>
</table>

During simulations, first of all, we tested two-level hierarchical procedures employing different combinations of two feature sets. The simulation results are presented in the first three columns of Table 3. For all the combinations in Table 3, it is shown that the hierarchical clustering structure performs better on average than the use of a single feature set individually or the use the composite feature vector (Table 2). This is due to the fact that hierarchical approach takes advantage of all the employed feature sets since only the samples that are clustered “best” with any of the feature sets are taken into account.

When SDH and wavelets are used at the first and second levels, respectively, it is observed that CCRs of Groups 1 and 4 are increased significantly while CCRs of Groups 2 and 3 are not increased by the same amount. When morphological features are used at the second level of the hierarchy (after SDH or wavelet features are employed at the first level), the improvement in CCRs of Groups 2 and 3 is also significantly higher than individual or composite use of feature sets (Table 2). Although CCR rates are higher in two-level hierarchical clustering schemes, the results were in accordance with the previous (i.e. single and composite use of features) results (Table 2), indicating that SDH and wavelets are more successful in classifying Groups 1 and 4 and morphological features are better suited to discriminating Groups 2 and 3. Simulations also showed that changing the order of textural and spectral features (i.e. wavelet features at Level 1 and SDH features at Level 2) does not alter CCR significantly. However, if morphological features are used at the first level of the hierarchy, CCR decreases since morphological features are designed specifically for challenging samples (i.e. samples containing veins and unified cohesive material), while textural and spectral features are more general. Moreover, classification time increases significantly if morphological features are used at the first level since the required time for extraction of morphological features is comparably long and this costly process has to be performed for all the samples at the first level.

Considering the simulation results discussed above, we can conclude that samples from Groups 1 and 4 are more likely to be clustered at levels where SDH and/or wavelets are used. On the other hand, samples from Groups 2 and 3 are more likely to be clustered at the level where morphological features are used. This does not mean that samples from Groups 2 and 3 are never clustered at levels employing SDH and wavelet features. However, challenging samples from these quality groups are best clustered at the level utilizing morphological features, which present a better feature space for separation of these samples. We observe that to obtain the best possible performance, SDH and wavelet features should be used prior to morphological features.

As another simulation example, a three-level hierarchical clustering scheme is tried out. The textural features are used at the first level, the spectral features are employed at the second level, and finally, the morphological features are used at the third level of the hierarchical clustering strategy. Performance results of this clustering process are presented in the last column of Table 3. The results attest that the proposed three-level design provides the highest CCR performance. In addition, changing the order of the first and second levels does not change CCR significantly. However, the morphological features should always be utilized at the third (and last) level because their use at lower levels (first or second) decreases CCR and increases processing time.

4. PLC controlled conveyor belt system

The marble classification procedure given in the previous section constitutes the software part of our complete system. On the other hand, to be able to employ the software part in marble industry, this study also aims the achievement of full control over the process of marble classification with a new electro-mechanical system that can be placed at the end of a production line. Accordingly, the hardware part of our system is responsible for controlling the complete mechanical structure in Fig. 8(a) by evaluating the results of the classification process.

Since this is an industrial application, the main controller should be immune to disturbances and noise [30]. Hence, a PLC (Fig. 8(c)) is chosen as the main controller in the system. PLC controls the entire system but needs a microcontroller for communicating with MATLAB. For this purpose, an AT89C52 microcontroller [31] is used. The mechanical structure also includes two pistons (Fig. 8(b)), a relay circuit (Fig. 8(d)), a 220 V panel required for the AC motor (Fig. 8(e)), and an air compressor required for the pistons (Fig. 8(f)).
The flowchart for detailing the functioning of the complete system is shown in Fig. 9. The operation of the system is as follows:

1. The conveyor belt runs and waits for a marble slab to enter into the image acquisition box.

2. When the marble slab enters the box, a sensor inside the box triggers the PLC input. After PLC takes that input, it stops the conveyor belt and activates one of its outputs for one of the pins of the microcontroller. The microcontroller reads this pin inside an infinite loop. This is done in order to prevent the bouncing effect. If the input does not change for a determined
duration, then it can be considered as the real input, otherwise it is considered as bouncing by the microcontroller.

(3) The microcontroller sends a signal to the serial port if the above conditions are satisfied. That signal is taken by MATLAB and causes an interrupt. This interrupt executes the callback function, which includes capturing of the image, running image processing and classification operations, and sending the result to the serial port.

(4) When the data coming from the serial port consist of the quality group information of the processed marble slab image, the microcontroller activates one of its outputs according to the determined quality group number. For this purpose, four microcontroller outputs are connected to the four PLC inputs providing one connection for each quality group. In accordance with the coming input data, PLC starts the conveyor belt, and after a pre-determined duration, it stops the conveyor belt again. The purpose of this operation is to bring the marble slab into the proper position for the pneumatic pistons (Fig. 8(b)).

(5) The system has two pistons having strokes of 500 mm. After the marble slab is brought into the proper position, PLC activates the pistons and the marble slab is pushed to the inclined loading ramp (Fig. 8(a)).

(6) A verification signal is needed after the marble slab is pushed to the inclined loading ramp. Four sensor pairs at the end of the ramp are employed for that purpose. When the marble slab passes through the correct ramp, and if there is no error or warning signals, the conveyor belt is started again and the system waits for the next marble slab.

There are one warning signal and one error signal in the system. The warning signal occurs when there is an overflow in one of the four quality groups. The counter blocks count the marble slabs and if the amount of marbles in one of the groups exceeds a pre-determined number, the system goes into overflow. The conveyor is stopped and the warning LED is activated. The error signal occurs when an unexpected error takes place in the system. This may happen if the marble slab goes to a wrong ramp due to a mechanical error. The conveyor belt is stopped again; all of the LEDs and a buzzer are activated.

For resetting the error and warning signals, two buttons are employed. Alternatively, in place of these buttons, the Supervisory Control and Data Acquisition (SCADA) software [32] can also be utilized (Fig. 10(a)). This is useful because the supervisor can monitor and control the system through a computer (a successful application of SCADA together with a PLC is presented in [33]). The system reset is used to reset the system completely. Besides SCADA, a Graphical User Interface (GUI) is designed for the operator to watch the process and control the image processing and classification operations (Fig. 10(b)). Initialization of the camera and the serial port, changing of the threshold value, and opening of the required software window can all be performed using the GUI. These two interfaces (SCADA and GUI) can be displayed in two different monitors for the operator to control both of them simultaneously.

One of the crucial parts of the conveyor belt system is the usage of the serial port interrupt with which the system runs faster and the use of the GUI in MATLAB becomes possible. Using infinite loops in MATLAB causes the system to run slower and does not allow watching the preview of the camera at GUI. The serial port enables us to use the preview property. The expected datum and the callback function that will be executed when the expected datum comes from the serial port are defined first. Until a datum comes from the serial port, the marble slab on the
conveyor belt is watched with the help of the preview property of MATLAB. After the expected datum comes, this operation is interrupted and the predefined callback function is executed. The image processing operations and classification algorithms are embedded in this callback function.

5. Summary and conclusions

A fully automated new electro-mechanical conveyor belt system for classifying surface images of marble slabs is presented. Design of software, hardware, and mechanical parts of the automatic marble classification system are explained and discussed. In this newly proposed system, a novel hierarchical clustering strategy is employed for quality classification without requiring a training set. Our large and diverse data set consists of 1158 images belonging to four quality groups. Correct classification rates of the proposed hierarchical clustering method have been obtained as 83.60% on average, and 85.41%, 81.26%, 82.13%, and 85.63% for Groups 1 through 4, respectively. It is also shown that the proposed hierarchical clustering strategy outperforms the approach that uses a composite feature vector by lumping different features together into a single feature vector. This performance improvement is accomplished by cascading features in a hierarchical manner and using them as input spaces for residual samples at each level of the hierarchy.

When the online method is used for updating cluster centers each time a new sample is classified, an increase in the correct classification rate is observed. This increase is around 3%, if a single feature (i.e. textural, spectral, or morphological) is used solely as the input of the clustering process. On the other hand, if the features are combined and used together with the proposed hierarchical clustering methodology, the online updating does not improve the system performance more than 1%. This means that using typical samples for each quality group to obtain cluster centers and fixing these cluster center values do not deteriorate the performance of our proposed hierarchical methodology. Moreover, this also indicates that the proposed hierarchical strategy improves the robustness of the classification process since the correct classification rate does not change much with small changes in cluster centers.

To check the effects on system performance, principal component analysis (PCA) [34] is used to reduce the computational burden and the principal components with a contribution equal to or greater than 0.1% are given as input to clustering algorithms. However, the results show a slight decrease in classification performance.

Simulations are also performed for different color spaces (i.e. KL, XYZ, and YIQ) since this is proven to be useful in [21]. However, paralleling the results in [22], no significant change has been noticed in classification performance. Thus, the RGB color space is used throughout the whole process.

Average feature extraction and clustering times (in seconds) for a sample using MATLAB® 2007b is measured to be 0.8062 for SDH, 1.3268 for wavelets, and 2.6671 for morphological features (Table 4). Together with all the required steps for classifying and grouping a marble sample, the system spends approximately between 1–4 s (see the last row of Table 4). This variation is based on how hard classifying a sample is. For a very challenging sample, all feature extraction methods would be executed one after another and thus the total required time would be cumulative. However, for an easily classified sample, there is no difference between the proposed approach and using a single clustering algorithm, provided that the clustering is performed at the first level of the hierarchy. These results can be considered acceptable for an online system that is to be employed in an industrial facility.

The inclined loading ramp design of the system is chosen among several possible designs. One can change this ramp with robotic arms, vacuum based carriers, or with a simple labeling machine that attaches stickers on marble slabs in line with the classification results.

The advantage of the developed electro-mechanical system over the existing ones is that full control over the whole process (i.e. classification using the developed software and sorting out of
the classified marble samples via a conveyor belt and control mechanisms) of marble classification is achieved instead of using only a software based visual inspection system. Thus, the complete system can be embedded into the production line of a marble factory to act as an element that allows the possibility of automatic quality classification of marble slabs.

It is our expectation that automated classification systems will be further improved and eventually employed in marble factories. If the classification currently performed by human experts can be successfully delegated to such automated systems, considerable increase can be expected in the production capacity and quality, together with an accompanying decrease in manufacturing costs.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.rcim.2010.07.004.

References