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Automatic classification of granite tiles through colour and texture features

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ABSTRACT

This paper is about the development of an expert system for automatic classification of granite tiles through computer vision. We discuss issues and possible solutions related to image acquisition, robustness against noise factors, extraction of visual features and classification, with particular focus on the last two. In the experiments we compare the performance of different visual features and classifiers over a set of 12 granite classes. The results show that classification based on colour and texture is highly effective and outperforms previous methods based on textural features alone. As for the classifiers, Support Vector Machines show to be superior to the others, provided that the governing parameters are tuned properly.
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1. Introduction

The natural stone industry has grown quite steadily over the last three decades. The slight setback suffered in 2008–2009 has been almost recovered in 2010, when worldwide production of raw and finished products amounted to approximately 50 million tons (Napoli, 2011). Within this sector granite accounts for about 60% of the overall production. The chief granite exporting countries, sorted by the share of export of raw and finished products, are: China (≈53%), India (≈16%), Brazil (≈8%), Italy (≈5%) and Spain (≈4%). In the building industry granite has become increasingly popular, due to a combination of strength, beauty and relatively affordable price. There are many commercial types of granite, which differ both in colour and texture. Traditionally, granite qualities are designated through a generic name which refers to the predominant colour (e.g.: 'Tobacco Brown', 'Zimbabwe Black', 'Emerald Pearl', etc.). Such denominations, however, may frequently change from one country to another. This problem has called for the definition of unified denomination criteria, partially solved by the European Standard EN12440 (2009). Yet this standard is by no means useful when we need to sort and grade granite products on the base of their visual appearance. Indeed, because of their natural origin, the visual appearance of granites with the same mineralogical content may differ significantly. As a consequence controversial situations between customers and suppliers may arise. It happens that the customer may dismiss a batch of tiles either because it is different from the sample that served as basis for the purchase, or because there is significant variation in the visual appearance within the batch. To avoid such problems, stone manufacturing companies have so far adopted visual inspection procedures which are mostly manual, carried out by skilled operators. Such approaches have been considered satisfactory for many years – though they are intrinsically qualitative, non-repeatable, and strongly subjective. But globalization has changed things quite a bit, calling for complex processes of organizational and infrastructural change aiming at maintaing high product and service standards. In an effort to survive – and even expand – in a highly competitive and globalised market, granite companies are therefore concerned with the development automatic systems to measure, compare and store the visual appearance of granite slabs in order to grade, sort, and retrieve them according to some similarity criteria. Among the possible advantages that such systems would provide we mention: (1) improvement in the quality control process through standard, objective and repeatable procedures; (2) reduction of sales returns and related economical losses; (3) better product traceability and warehouse management.

In this scenario the contribution of this paper is to give some insight into the development of an expert system for automatic grading of granite tiles. To this end we consider different visual descriptors and classifiers and evaluate their performance in granite grading tasks. The remainder of the paper is organized as follows. After a review of related literature (Section 2), we give a description of the materials used in our research (Section 3) and of the methods to extract and classify visual features (Section 4). In Section 5 we describe a classification experiment to evaluate the performance of the proposed approaches. The results are presented and discussed in Section 6. Section 7 concludes the paper with some final considerations.

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2. Related research

Automatic classification of product into lots of similar visual appearance – a problem sometimes referred to as *grading* – has found interesting applications in many industrial products, such as *paper* (Turtinen, Pietikäinen, & Silvén, 2006; Maldonado & Graña, 2009), *ceramic tiles* (Boukouvalas, Kittler, Marik, & Petrou, 2000; Kukkonen, Kälviäinen, & Parkkinen, 2001; Jiaoyan, Di, & Xuefeng, 2004), *leather* (Hoang, Wen, Nachimuthu, & Jiang, 1997; Yeh & Perng, 2001), *metal coils* (Zhang, Ding, Lv, Shi, & Liang, 2011), *fabric* (Bennamoun & Bodnarova, 2003; Semnani & Sheikhzadeh, 2009; Liang, Bingang, Chi, & Feng, 2012) and *painted slates* (Ghita, Whelan, Carew, & Nammalwar, 2005).

As for applications to natural stone products, we notice that an increasing number of approaches has been presented in the last years, thus testifying a growing interest in the field. On the whole we can divide the methods in two groups: those based on image processing and those based on spectrophotometric data. The methods of the first group can be further subdivided in two sub-groups: those based on texture features alone and those based on a combination of colour and texture.

Literature review shows that methods based on texture features alone are the majority. Dogan and Akay (2010) recently proposed a system for automatic classification of marble slabs based on sum and difference histograms and AdaBoost. The authors report high classification accuracy on an experiment based on four different marble classes. Topalova and Tzokev (2010) presented a method for grading of surface tiles based on gray-scale histograms reporting good accuracy on a classification task involving four classes and five brightness variations. Similar texture features were also used in a work of Carrino, Polini, and Turchetta (2002) for automatic classification of a specific type of marble, the 'Rosa Perlato of Coreno'. Other texture descriptors have also been succesfully used in the past. Kurmyshev, Sánchez-Yáñez, and Fernández (2003) described an application based on the coordinated clusters representation (CCR) for quality control of polished granite tiles of the type 'Rosa Porriño'. Bianconi and Fernández (2006) employed different Gabor filter banks for granite classification. Classification of marble surfaces has been also approached with scale-space (Dislaire, Pirard, & Vanrell, 2004) and wavelets (Luis-Delgado, Martínez-Alajarín, & Tomás-Balibrea, 2003).

If compared with the previous sub-group, application of combined colour and texture features for classification of natural stone products has received less attention. Approaches are in fact quite few, and, to the best of our knowledge, all based on the same idea: applying grey-scale texture descriptors to each colour channel separately. In a recent work Ershad (2011) described a method based on a morphological operator (Primitive Pattern Units) applied to each colour channel separately to discriminate among four different classes of natural stone. Likewise, Martínez-Alajarın, Luis-Delgado, and Tomás-Balibrea (2005) used sum and difference histogram features extracted from each colour band separately and neural networks to classify marble slabs into three categories, according to their quality. Gabor filtering on each colour band separately was proposed by Lepistö, Kunttu, and Visa (2005) for classification of four classes of granite-like rock images.

In the second group of methods the source of information is represented by spectrophotometric data. The approach proposed by López, Martínez, Matías, Taboada, and Vilán (2010) belongs to this group. The manuscript, however, neither details which spectral features are used nor how they are obtained, making it difficult to replicate the experiments. A similar method is described in the work of Araújo, Martínez, Ordóñez, and Vilán (2010). Here the authors are concerned with the identification of different granite varieties. To this end they employ a contact spectrophotometer to capture spectral data at 10 different randomly-chosen locations from each granite specimen and use functional SVM for classification. In our opinion a potential limit to these methods might be the scarce capability of a spectrophotometer – which is basically a point-by-point, not full field instrument – to capture the local variation in appearance (i.e.: texture) typical of natural stones.

This brief review reveals that most of the approaches described in literature are based on textural features alone. This is somewhat surprising, since the appearance of natural stone products – particularly that of granite – strongly depends on both texture and colour. A limited number of methods including colour do in fact exist, but they are all based on the same idea, namely extracting texture features from each colour channel separately. Based on these consideration, and starting from recent theoretical and experimental advances in colour-texture analysis, in the following sections we propose and discuss some new ideas and solutions.

3. Materials

We considered, in this work, a group of 12 commercial classes of granite. Each class is represented by four tiles, so the overall lot is composed of 48 pieces (Fig. 1). The materials have been kindly provided by *Mondial Marmi S.r.l.*, a stone manufacturing company based in Perugia, Italy. This dataset is quite challenging, since it contains granite classes that are very similar in appearance and difficult to distinguish even to a trained eye (e.g.: 'Acquamarina' and 'Azul Capixaba'; 'Rosa Porriño A' and 'Rosa Porriño B').

Images of each tile have been captured through an acquisition system composed of a dome illuminator (Monster Dome Light 18.25"), a commercial camera (Samsung S850) and a base. The camera is fixed to the dome, which is mounted on the base. The base permits to mount the dome at different rotation angles, making it possible to capture hardware-rotated images. Inside the base there is a pocket into which tiles are placed for acquisition. Further details and drawings about the imaging apparatus are provided in Fernández, Ghita, González, Bianconi, and Whelan (2011); MondialMarmi (2011). The acquisition process was carried out in our lab at the Department of Industrial Engineering of the University of Perugia, Italy. Throughout the imaging process the shutter speed, aperture size and ISO value of the camera were set at 1/30 s, 7.4 and 50, respectively, and maintained constant. In order to discard distortion in the periphery of the acquired images, we ultimately retained a central area of 544×544 pixels, which corresponds to a tile area of about 20×20 cm^2. All the images of the dataset can be freely downloaded from the internet (MondialMarmi, 2011).

4. Methods

As we mentioned in Section 2, since granite appearance is mainly determined by colour and texture, it seems reasonable to rely on these two properties for grading and classification tasks. Whether texture and colour should be treated separately or jointly has been debated at length in literature (Drimbarean & Whelan, 2001; Mäenpää & Pietikäinen, 2004), and several approaches have been proposed. To be useful in practical applications, a method should provide high classification accuracy along with low dimensionality and computational cost. This reduces the number of approaches that translate into practical applications and, at the same time, puts the designer of the expert system into trouble when it comes to choose the most suitable strategy. In a recent survey Bianconi, Harvey, Southam, and Fernández (2011) evaluated an ample set of colour texture descriptors for image classification purposes. In their study the authors compare different strategies to

Fig. 1. The 12 granite classes used in the experiments.

integrate texture and colour data, and set into evidence a reduced group of descriptors which provide high classification accuracy along with low dimensionality and computational cost. They make up a set of six methods (Table 1) that can be considered 'optimal' in the Pareto's sense. These are the methods that we used herein. In Section 4.1 we recall the basics of each colour texture descriptor and refer the reader to the above cited work for details and technicalities. Then, in Section 4.2, we discuss five different classification strategies that can be used to implement the expert system.

Before going into the methods, we would like to discuss some issues related to robustness against noise factors. These represent significant concerns in practical applications and are mainly related to changes in illumination and viewing conditions (i.e.: rotation and scale). In this work we assume that noise sources like changes in illumination and image scale can be removed by keeping both illumination and camera/object distance constant throughout the acquisition process. Such conditions can be easily obtained in a factory, for instance through an acquisition system similar to the one described in Section 3. In contrast, changes in rotation are virtually impossible to eliminate or compensate for, since granite texture in the tile can occur, in principle, at any orientation. For this reason all the descriptors presented here below are rotationally-invariant, as discussed and experimentally confirmed in a previous work (Bianconi et al., 2011).

4.1. Colour texture descriptors

The methods presented from Section 4.1.1 through Section 4.1.4 are based on disjoint colour and texture analysis. This means that textural features are extracted from images previously converted to grey-scale, while colour features are computed separately. Textural and chromatic features are concatenated into the same feature vector. These approaches are usually referred to as *parallel* methods (Palm, 2004). Recent experiments (Bianconi et al., 2011) suggest that this strategy seems to be the most promising to integrate textural and colour data. This results seems to be supported by some recent psychophysiological findings which indicate that colour and texture are processed independently in the brain (Cant, Large, McCall, & Goodale, 2008; Cavina-Pratesi, Kentridge, Heywood, & Milner, 2010). The last two methods (Sections 4.1.5 and 4.1.6) are based on different strategies, which are usually referred to as *intra-channel* analysis, where features are extracted from each colour channel separately; and *intra-* and *inter-channel* analysis, where features are extracted both from each colour channel separately and from couples of colour channels jointly.

Table 1
Colour texture descriptors used in the experiments.

Method	Dimension	Reference
Co-occurrence matrices + chromatic features	9	(Arvis et al., 2004)
Co-occurrence matrices + colour percentiles	14	(Niskanen et al., 2001)
Gabor features + chromatic features	36	(Drimbarean & Whelan, 2001)
Local Binary Patterns + percentiles	45	(Niskanen et al., 2001)
Intra-channel Gabor features	96	(Paschos, 2001)
Integrative Co-occurrence matrices	30	(Arvis et al., 2004; Palm, 2004)

4.1.1. Co-occurrence matrices + chromatic features

The use of co-occurrence matrices and chromatic features has been originally proposed by Arvis, Debain, Berducat, and Benassi (2004). The method is based on the eight co-occurrence matrices corresponding to one-pixel displacements along the following eight directions: $\{0°, 45°, \ldots, 315°\}$. The matrices are averaged for rotation invariance and five statistical features are extracted from each matrix, namely: contrast, correlation, energy, entropy and homogeneity. Each feature is normalized in the $[0,1]$ interval. Chromatic features are the mean and standard deviation of the hue and saturation channels. Both channels are normalized in the $[0,1]$ interval. The method generates nine features; five monochrome and four chromatic features.

4.1.2. Co-occurrence matrices + percentiles

Combination of co-occurrence features and colour percentiles has been proposed by Niskanen, Silvén, and Kauppinen (2001) for applications in wood inspection. Gray-scale co-occurrence features are computed as described in the preceding section. Chromatic features are the first, second and third quartile of each R, G and B channel (each channel is normalized between 0 and 1). The method produces 14 features; five textural features and nine chromatic features.

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4.1.3. Gabor features+chromatic features

This approach employs Gabor filters to extract textural features from images previously converted to gray-scale (Drimbarean & Whelan, 2001) . In the implementation adopted herein, we used a bank of filters with the following parameters: number of frequencies = 4, number of orientations=6, maximum frequency = 0.327, frequency ratio = half – octave, and smoothing parameters η, γ = 0.5. These settings are based on the results presented in a previous work (Bianconi & Fernández, 2007). Texture features are the mean and standard deviation of the absolute value of each transformed image. As a result we get 48 textural features. Discrete Fourier transform (DFT) normalization, which we apply to achieve invariance against rotation (Lahajnar & Kovacic, 2003), reduces this number to 32. These features are then concatenated with the four chromatic features computed as in Section 4.1.1. The dimension of the resulting feature vector is 36.

4.1.4. Local Binary Patterns + percentiles

In the same way as co-occurrence matrices and Gabor filters, one can employ other grey-scale texture descriptors, such as LBP, to extract textural features. This descriptor has proven effective in a wide range of industrial applications (Nanni, Lumini, & Brahnam, 2012). The method presented in this section, described by Niskanen et al. (2001), indeed concatenates LBP features extracted from grey-scale images and colour percentiles computed on each R, G and B channel. In our implementation we used the $LBP^{ri}_{8,1}$ operator to obtain rotationally-invariant features. These are concatenated with colour percentiles, which are computed as in Section 4.1.2. The resulting feature vector contains 45 features: 36 monochrome rotationally-invariant features and nine colour features.

4.1.5. Intra-channel Gabor features

The use of Gabor features extracted from each R, G and B channel separately has been proposed by Paschos (2001) and Lepistö et al. (2005). Using the same filter bank described in Section 4.1.3 the method generates 144 monochrome features. Rotationally-invariant features are obtained through normalization, which reduces the total number of features to 96.

4.1.6. Integrative co-occurrence matrices

Integrative co-occurrence matrices (Arvis et al., 2004; Palm, 2004) are based on both intra- and inter-channel features which are computed by extracting the same co-occurrence features described in Section 4.1.1 from each channel separately and from the following couples of colour channels jointly: (R, G), (R, B) and (G, B). The method generates five features for each single channel and each couple of colour channels giving a total of 30 features.

4.2. Classifiers

The classification step involves the design/selection of a suitable classifier and, depending on the chosen classifier, the selection/tuning of one or more parameters. When designing expert systems this is a crucial step, and the result is often a trade-off among various factors, such as: easiness of implementation, accuracy, computational demand and robustness. Herein we considered five well-established classifiers (Table 2), namely: Nearest Neighbourhood (NN), Nearest Mean Classifier (NMC), Naïve Bayes (NB), Linear classifier (LLS) and Support Vector Classifier (SVC). In the following subsections we recall the basics of each approach and briefly discuss the pros and cons.

Table 2
Classifiers used in the experiments.

Classifier	Abbrv.	Implementation	Notes
Nearest Neighbour	NN	PRTools 4.1	L_2 distance
Nearest Mean Classifier	NMC	PRTools 4.1	L_2 distance
Linear	LLS	PRTools 4.1	One-against-all strategy Least squares estimation
Naïve Bayes	NB	Custom	Gaussian pdf
Support Vector Classifier	SVC	STPRtool	One-against-all strategy RBF kernel

4.2.1. Nearest neighbour and nearest mean classifier

The first two approaches are based on distance, which, in our implementation, is the Euclidean (L_2) in both cases. An unknown pattern is assigned the label of the nearest training pattern (NN) or that of the nearest centroid (NMC[2]). The advantages of both methods are that they are parameter-free, easy to implement and computationally cheap. Potential disadvantages are sensitivity to outliers in the case of NN, whereas, as for NMC, centroids can be scarcely representative in presence of high intra-class variability and therefore misclassifications can arise.

4.2.2. Naïve Bayes

The Naïve Bayes classifier derives directly from Bayes' theorem under the hypothesis that individual features are statistically independent (Theodoridis & Koutroumbas, 2006). In the training step a probability density function is estimated for each class and each feature. In this phase one can assume a predefined functional form for the pdf – herein we assumed a normal distribution – and therefore the step reduces to learning the parameters (mean and standard deviation in this case) of such distribution for each class and feature. In the classification step, given and unknown pattern, posterior class probabilities resulting from each features are multiplied together and the pattern is assigned the class with the highest product. Despite the assumption of statistical independence, which rarely holds, the method turns out to be quite effective in practice (Hand & Yu, 2001).

4.2.3. Linear classifier

The linear classifier, originally developed for binary classification problems, seeks the linear function (hyperplane) that best separates the classes in the feature space. Obviously the optimal solution (perfect separation between classes) exists only if the two classes are linearly separable. Different strategies exist to find the separating hyperplane. One is least squares error estimation, which is the approach adopted here. In this case the procedure determines the hyperplane that minimizes the weighted classification error (i.e. number of misclassified patterns $\times$ distance to the hyperplane) (van der Heijden, Duin, de Ridder, & Tax, 2004). Other methods include perceptron learning and Fisher's linear discriminant (Duda et al., 2001). As for extension to multi-class, we adopted the one-against-all strategy, where there is one linear function per class which is trained to classify between the samples of that class from the samples of all remaining classes.

4.2.4. Support vector classifier

Support Vector Machines are considered highly effective classifiers, and are currently held in great esteem in the pattern recognition community. The design of a support vector classifier, however, is not straightforward and needs to be handled with care. The process involves the choice of a kernel function – through which patterns are mapped into a higher-dimensional space – and of the related parameters (Schölkopf & Smola, 2002). According to Hsu, Chang, and Lin (2010) an RBF kernel is a reasonable choice in most cases, particularly when the number of features is not excessively

[2] This method is also referred to as Minimum Distance Classifier (Duda, Hart, & Stork, 2001).

large. Since we have to deal with relatively few features (at most 96 – see Table 1), this choice seems appropriate for the application studied herein. The parameters that govern this kernel, namely C and γ, however, are not known beforehand and need to be selected carefully. In Section 5.1 we propose a procedure for fast estimation of both.

5. Experiments

In the experimental part we estimated the accuracy of the methods presented in Section 4 through a supervised image classification task. We considered all the 30 possible combinations colour texture features/classifiers.

As a preliminary step, the images of the original dataset (Fig. 1) have been subdivided into 16 non-overlapping sub-images, resulting in a dataset of 64 samples per class. Estimation of accuracy is based on stratified sampling: the whole dataset is randomly split into two disjoint sub-sets, one for training and the other for validation, with the constraint that the fraction of samples used for training is the same for each class. Each classifier is build on the training samples and its accuracy is estimated on the test samples. This is the percentage of images of the validation set which are classified correctly. To get a stable estimate the procedure is averaged over 100 different subdivisions into training and validation set.

We believe it is particularly interesting to evaluate the sensitivity of the methods to the number of samples used for training, since in practical applications one may have only few samples to train the classier. To this end we repeated the experiments using three different proportions between training samples and total number of samples, namely 1/2, 1/4 and 1/8. These correspond to 32, 16 and 8 training samples per class, respectively.

5.1. Estimation of SVM parameters

As we mentioned in Section 4.2.4, SVM parameters need to be tuned carefully, since the performance of the classifier strongly depends on them. Hsu et al. (2010) recommend a grid-search procedure where various pairs of (C,γ) are tried and the one with the best cross-validation accuracy is selected. This method, however, is computationally very demanding and therefore not recommendable for practical applications. Instead we propose a simplified procedure based on two sequential steps: in the first step we estimate C and in the second γ. Estimation of C is based on measuring the dispersion of the input data and does not require cross-validation. The basic idea is that the value of C should be large enough compared to the diameter of the sphere containing the input data, as suggested by Chapelle, Haffner, and Vapnik (1999). This parameter that can be computed easily from the training data. For the dataset considered herein, the different colour texture descriptors show similar dispersion (mean radius of the minimum enclosing ball = 13,66 ± 2,74), therefore we considered that $C = 100$ would be a reasonable choice with all the colour texture descriptors considered in the paper. In the second step, with the value of C fixed, an optimal value for γ is searched over the set of predefined values suggested by Hsu et al. (2010), namely $[2^{-15},2^{-13},\ldots,2^{3}]$. In this step cross-validation is performed by randomly picking 50% of the patterns whole dataset. The process is repeated 100 times and at the end we retained the value of γ that most frequently gave the best accuracy considering all the colour texture descriptors. The result, in this case, is $\gamma = 2^{-3}$.

5.2. Implementation, execution and reproducible research

All the colour texture descriptors and classifiers presented in Section 4 have been coded in MATLAB® R14. Nearest neighbour, nearest mean and linear classifier are based on PRTools (van der Heijden et al., 2004). Support vector classifier is based on STPRtool (Franc & Hlävac, 2004). For reproducible research purposes, data and code required to replicate the experiments are available in Ref. GR-CLASS (2012).

Table 3
Results of the classification experiment.

Descriptor	Classifier				
	NN	NMC	LLS	NB	SVC
Training samples/total samples = 1/2					
Cooc-m + chromatic features	95,2	87,7	88,6	94,6	97,3
Cooc-m + percentiles	93,2	82,9	88,9	87,3	96,3
Gabor + chromatic features	88,1	65,1	90,3	75,3	95,5
LBP + percentiles	94,0	83,5	89,8	76,9	97,2
Intra-channel Gabor features	92,3	79,6	88,3	91,4	97,3
Integrative cooc-m	95,5	85,4	95,2	91,6	98,5
Training samples/total samples = 1/4					
Cooc-m + chromatic features	93,4	87,9	87,8	94,2	96,3
Cooc-m + percentiles	91,1	82,8	88,0	86,6	94,9
Gabor + chromatic features	84,6	65,6	80,0	73,4	93,4
LBP + percentiles	92,3	83,5	87,3	51,7	96,1
Intra-channel Gabor features	89,7	79,9	84,7	90,6	96,0
Integrative cooc-m	93,8	85,6	93,6	91,1	97,1
Training samples/total samples = 1/8					
Cooc-m + chromatic features	90,8	87,3	86,8	92,5	94,1
Cooc-m + percentiles	88,4	81,8	86,8	84,5	92,1
Gabor + chromatic features	79,1	65,7	78,2	69,0	89,1
LBP + percentiles	89,8	82,5	80,5	31,3	93,6
Intra-channel Gabor features	86,3	79,8	76,2	87,8	93,1
Integrative cooc-m	90,8	84,9	87,2	89,2	94,6

6. Results and discussion

The results (Table 3) show that the methods considered in this paper provide high granite classification accuracy, and therefore represent viable approaches for granite grading tasks. The experiments indicate that in this domain combination of colour and texture features outperforms classification based on grey-scale texture features alone (Fernández et al., 2011). This result is in agreement with current literature in the field (Drimbarean & Whelan, 2001).

With respect to the visual descriptors, the results set into evidence the good performance of co-occurrence matrices, both in the disjoint colour and texture version (co-occurrence matrices + chromatic features) and in the intra- + inter-channel version (integrative co-occurrence matrices). Moreover, in both cases such good results are obtained with quite few features (9 and 30, respectively).

Regarding the classifiers, we notice that SVC provides good results with almost all the colour texture descriptors, even with few training samples. This result, however, strongly depends on a preliminary tuning step needed to adjust the kernel parameters C and γ. Another potential drawback of this classifier is that it is significantly slower that the others. The nearest neighbour classifier also provides good accuracy, though significantly lower than that obtainable with SVC. On the other hand, NN is fast and parameter-free. This method is therefore a good substitute when preliminary parameter tuning is not possible. The other classifiers provide, on average, lower accuracy.

A specific comment deserves the trend shown by LBP + chromatic features with the Naïve Bayes classifier, since this appears significantly lower and peculiarly different from that of the other methods. In our opinion this behaviour is closely related to the intrinsic nature of LBP, which produces a highly uneven feature vector where some bins tend to have a prior probability much higher than others (Bianconi & Fernández, 2011). As a result the estimation of pdf which the classifier requires may be unstable, especially when few training samples are used.

7. Conclusions

In this paper we have presented some possible approaches to the development of an expert system for automatic classification of granite tiles. Based on recent results on colour texture analysis, we have proposed a set of visual descriptors which provide good classification accuracy with a limited number of features. We have also evaluated the performance of five different classifiers and discussed the pros and cons of each. All the solutions presented in the paper – of which we provide a full-functional implementation in MATLAB® – are easy to implement and computationally cheap.

The results show that good classification accuracy (> 90%) can be obtained with few features and limited number of training samples. This result can be further improved (> 94%) using a support vector classifier, provided that its parameters are tuned properly. To this end we presented a quick and easy procedure to estimate SVM parameter avoiding time-consuming procedures.

Throughout the paper we have assumed that the imaging system works under invariable illumination and scale conditions. We can safely assume that such conditions can be easily obtained in practical implementations. We would like to emphasize, however, that the first condition is particularly critical to the system. The reader should be aware that classification accuracy may drop drastically in presence of variable illumination.

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