Selection of Color Texture Features from Reduced Size Chromatic Co-occurrence Matrices

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***Abstract*—In this paper, we present a feature selection scheme which builds a low-dimensional feature space for texture classification. These features are extracted from texture descriptors called Reduced-Size Chromatic Co-occurrence Matrices (RSCCMs) which result from color quantization. Thanks to experimental results achieved with VisTex and OuTex databases, we show that the analysis of Haralick features extracted from these RSCCMs, themselves computed from color images coded in 28 different color spaces, provides satisfying classification results while significantly reducing the processing time.**

I. Introduction

Color texture classification is a major field of development for several industrial vision applications [1]. These applications generally require that the processing time of texture classification scheme has to be as short as possible in order to respect real-time constraints. To classify color textures, three kinds of features are used:

- "luminance based texture features" mixed with color statistical features [2], [3],
- "within color component texture features" which take into account only the spatial relationships within a single color component (for example within the color component R, G or B) [4], [5], [6],
- "between color component texture features" which consider spatial relationships within and between different color components [7], [8], [9].

Even if the two first approaches seem to be computationally fast, they do not take into account the spatial relationships between color components. So, the information on the whole color texture is lost and the classification quality is reduced [7]. That is why several authors privilege features which consider spatial relationships within and between different color components. One of the most well known and widely used descriptors which consider spatial relationships between color components, is the Chromatic Co-occurrence matrix (CCM) [7], [8], [9]. In spite of the good classification results obtained by the analysis of CCMs, this descriptor is often criticized because of its memory storage cost. That is why color texture features, like Haralick ones, are extracted from CCMs in order to characterize textures. However, the computation of those features is time consuming.

Furthermore, we have shown that the analysis of features extracted from images coded in several color spaces improves the texture classification rates [9]. Though, this strategy increases the number of texture features. It is well known that the analysis of a high number of features which may be correlated or not discriminating, decreases the quality of the classification while increasing the processing time.

To decrease the Haralick feature computation time and the classification time, we propose, in the one hand, to reduce the number of colors in the image thanks to a color quantization scheme and, in the other hand, to reduce the number of necessary color texture features thanks to a sequential feature selection procedure. Moreover, the selection of texture features may improve the quality of classification.

For these purposes, we first introduce the Reduced-Size CCMs (RSCCMs) which result from color quantization of images coded in color spaces. Then, we present a feature selection scheme which builds a low-dimensional feature space for texture classification. We show that the analysis of Haralick features extracted from these RSCCMs, provides satisfying classification results while significantly reducing the processing time. Our attention is also devoted to the relationships between RSCCMs and feature selection performed during a supervised learning.

In the second section of this paper, we present how the color properties of pixels can be represented in different color spaces and how the color components of pixels are quantized to produce the RSCCMs. In the third section, we describe color texture features extracted from RSCCMs. Section IV details the texture classification method based on a sequential selection of a low dimensional feature space. Finally, experimental results achieved with VisTex and OuTex databases show that the proposed method increases the rate of well-classified images while significantly reducing the processing time of the classification scheme.

II. Color representation

A. Color spaces and texture analysis

A color camera provides a color image where each pixel is characterized by three color components R, G and B. However, color analysis is not restricted to the (R, G, B) acquisition color space because there exists a large number of color spaces which respect different properties [10]. Drimbarean or Palm have compared the performances reached by color texture classification schemes using different color spaces [4], [8]. The synthesis of these works does not allow to conclude on the definition of a single color space which is well suited to the classification of all the color textures, but shows that classification results can be improved by using different color spaces.

In order to take into account the properties of different color spaces, Chindaro proposes to merge different classifiers where the images are coded in different color spaces [11]. Likewise, Vandenbroucke selects statistical features, which are computed from different color components [12].

So, in this paper we propose to characterize textures by extracting features from color images coded in different color spaces. These spaces can be classified into four families: the primary color spaces, the luminance-chrominance color spaces, the perceptual color spaces and the independent color component spaces [13]. Figure 1 shows how these families can be divided into subfamilies.

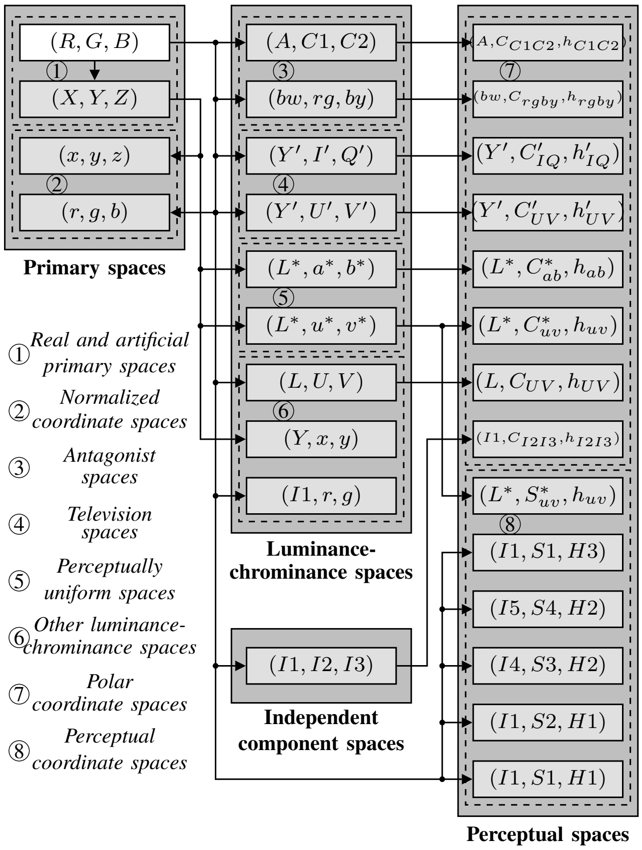


Fig. 1. Color space families.

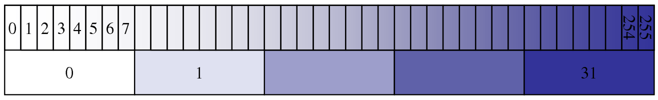


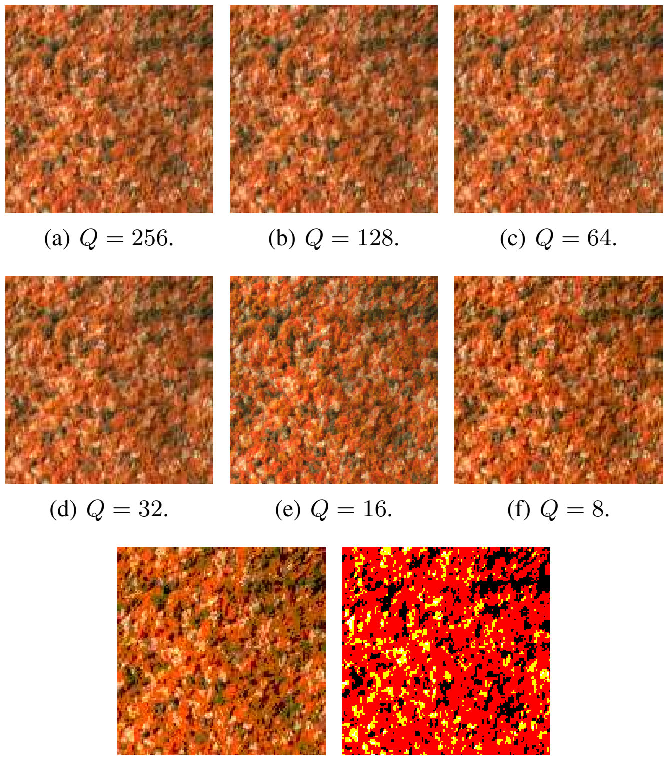
Fig. 2. Uniform sub-quantization in $Q = 32$ levels.

The originality of the proposed approach is to extract color texture features not only from images coded in a single color space but from images coded in the $N_S = 28$ color spaces of figure 1 in order to take advantage of each of them and to improve the quality of texture classification.

B. Color Quantization

The color of each pixel is represented by three color components C_1, C_2 and C_3. Each of these components is generally coded with 8 bits and so quantized with $Q = 2^8 = 256$ levels. Thus, the color component levels range from 0 to $Q-1$ and the number of available colors reaches $Q^3 = 16\ 777\ 216$. To reduce the number of colors within the image, we choose to apply the uniform color quantization method which consists in uniformly digitizing the color components of a color space [7]. Figure 2 illustrates this method to quantize each color component with $Q = 32$ levels.

Figure 3 shows the application of this quantization scheme on the VisTex image 3(a) whose color components are initially coded with $Q = 256$ levels [14].



(a) $Q = 256$. (b) $Q = 128$. (c) $Q = 64$.

(d) $Q = 32$. (e) $Q = 16$. (f) $Q = 8$.

(g) $Q = 4$. (h) $Q = 2$.

Fig. 3. Uniform color quantization of the image 3(a) coded in the (R, G, B) color space.

By visualy examining the quantized images, we notice that the color texture is relatively well preserved while Q is higher than or equal to 8. So, it would be interesting to measure the influence of quantization on the performances of color texture classification by means of CCM analysis.

However, the originality of our contribution does not deal with color quantization problem. In this paper, we show that it is possible to use CCM for color texture classification with both a low computation time and very satisfying classification results. For this purpose, we suggest to reduce the size of CCM thanks to a color quantization scheme and to select a reduced number of discriminating color texture features thanks to a feature selection procedure, as we will see in the next sections.

III. Color texture features extracted from RSCCMs

A. Chromatic co-occurrence matrix (CCM)

The CCM, introduced by Palm [8], is a statistical texture descriptor which both measures the color distribution in an image and considers the spatial interactions between the colors of pixels.

Let C_k and $C_{k'}$, be two of the three color components of a color space denoted (C_1, C_2, C_3) $(k, k' \in \{1, 2, 3\})$ and let $M_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}]$, be the CCM which measures the spatial interactions between the color components C_k and $C_{k'}$ of the pixels in the image $\mathbf{I}$, according to the neighborhood $\mathcal{N}$. The cell $M_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}](i, j)$ of this matrix contains the number of times that a pixel P whose color component value $C_k(P)$ is equal to i, is the neighbor, according to the neighborhood $\mathcal{N}$, of a pixel P' whose color component value $C_{k'}(P')$ is equal to j. As it measures the local interaction between pixels, the CCM is sensitive to significant differences of the image size. To decrease this sensitivity, it is necessary to normalize the CCM by the total co-occurrence number. Let $m_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}]$, be the normalized $M_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}]$ CCM:

$$m_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}] = \frac{M_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}]}{\sum_{i=0}^{Q-1}\sum_{j=0}^{Q-1} M_{\mathcal{N}}^{C_k,C_{k'}}[\mathbf{I}](i,j)}. \qquad (1$$

For a given image $\mathbf{I}$ and a given neighborhood $\mathcal{N}$, $N_M = ($ CCMs are thus computed:

- three within color component matrices denoted $m_{\mathcal{N}}^{C_1,C_1}[\mathbf{I}]$, $m_{\mathcal{N}}^{C_2,C_2}[\mathbf{I}]$, $m_{\mathcal{N}}^{C_3,C_3}[\mathbf{I}]$,
- three between color component ones denoted $m_{\mathcal{N}}^{C_1,C_2}[\mathbf{I}]$, $m_{\mathcal{N}}^{C_1,C_3}[\mathbf{I}]$ and $m_{\mathcal{N}}^{C_2,C_3}[\mathbf{I}]$.

B. Reduced size chromatic co-occurrence matrix (RSCCM)

To reduce the amount of information while preserving the relevance of the CCMs, we propose to apply color quantization before computing them. When Q is equal to 256, the full size matrix is called CCM. When Q is lower than 256 thanks to color quantization, 6 Reduced-Size CCMs (RSCCMs) are computed. Since the size of each RSCCM is $Q \times Q$, reducing the quantization level allows not only to decrease the memory storage cost, but also the computation time required to extract texture features.

C. Haralick features

Moreover, four neighborhoods based on four different directions respectively (0^o, 45^o, 90^o, 135^o) and a spatial distance v separating the considered pixel from the neighbors, are usually used to compute direction-dependent co-occurrence matrices [15]. Figure 4 shows these neighborhoods.

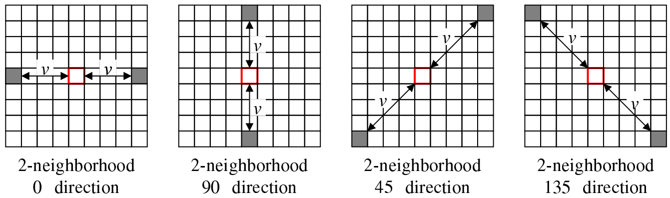


Fig. 4. 3x3 neighborhoods in which neighboring pixels are labeled as gray.

For color texture classification, Palm has proposed to extract Haralick texture features from each of the 6×4 CCMs [8]. In order to be rotationally invariant, the mean and the variance of the extracted features are computed. In order to reduce the number of matrices, we propose to use another approach which consists in extracting the Haralick features from RSCCM computed with only one well suited neighborhood. Indeed, computing only one RSCCM instead of computing four direction-dependent ones, reduces the memory storage cost and the computation time. It has been proved that the choice of the neighborhood shape used to compute CCM depends on the analyzed textures [10]. When textures do not present any privileged direction, it is necessary to compute features which take into account all the possible directions. That is why we choose to use the isotropic 8-neighborhood in order to take into account all directions, and the distance v is set to 1 [5], [7]. Figure 5 shows this neighborhood.

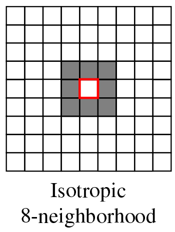


Fig. 5. Isotropic 8-neighborhood.

IV. Color texture supervised classification

Our scheme is divided into two successive stages:

- a supervised learning stage selects discriminating texture features among a set of available ones,
- a texture classification stage classifies textures by considering only the so-selected features.

A. Candidate color texture features

The supervised learning scheme examines N_ω learning images $\omega_{i,j}$ $(i = 1, \ldots, N_\omega)$ associated with each of N_T texture classes T_j $(j = 1, \ldots, N_T)$. Each image $\omega_{i,j}$ is coded in the $N_S = 28$ color spaces shown by Fig. 1. $N_M = 6$ RSCCM are then computed from each of the $N_S = 28$ coded images and $N_H = 14$ Haralick features are extracted from each matrix. We thus examine $N_f = N_H \times N_M \times N_S = 14 \times 6 \times 28 = 2352$ color texture features denoted $x_{i,j}^f$, $f = 1, \ldots, N_f$, characterizing each learning image.

Since the total number N_f of color texture features is very high, it is necessary to select the most discriminating ones in order to reduce both the size of the feature space and the classification time. Furthermore, the feature selection may increase the quality of classification.

B. Feature selection

The determination of the most discriminating feature space is achieved thanks to a sequential feature selection procedure based on a supervised learning scheme. This non-exhaustive procedure has given very good results for color image segmentation [12].

At each step s of this procedure, an informational criterion J_s is evaluated in order to measure the discriminating power of each candidate feature space. At the beginning of this procedure ($s = 1$), the N_f one-dimensional candidate feature spaces, defined by each of the N_f available color texture features, are considered. The candidate feature which maximizes J_1 is selected at the first step. It is associated in the second step of the procedure ($s = 2$) with each of the $(N_f - 1)$ remaining candidate color texture features in order to constitute $(N_f - 1)$ two-dimensional candidate feature spaces. We consider that the two-dimensional space which maximizes J_2, is the best space for discriminating the texture classes…

In order to only select color texture features which are not correlated, we measure, at each step $s \geq 2$ of the procedure, the correlation level between each of the available color texture features and each of the $(s-1)$ other color texture features constituting the previously selected $(s-1)$-dimensional space. The considered features will be selected as candidate ones only if their correlation level with the already selected color texture features is lower than a threshold fixed by the user [12].

We assume that the more the clusters associated with the different texture classes are well separated and compact in the candidate feature space, the higher the discriminating power of the selected color texture features is. That leads us to choose measures of class separability and class compactness as measures of the discriminating power.

At each step s of the procedure and for each of the $(N_f - s + 1)$ s-dimensional candidate feature spaces, we define a color texture feature vector $X_{i,j} = [x_{i,j}^1, ..., x_{i,j}^s]^{\mathrm{T}}$, where $x_{i,j}^s$ is the s^{th} color texture feature for the i^{th} learning image $\omega_{i,j}$ ($i = 1, \ldots, N_\omega$) associated with the texture class T_j ($j = 1, \ldots, N_T$).

The measure of compactness of each texture class T_j is defined by the within-class dispersion matrix Σ_C:

$$\Sigma_C = \frac{1}{N_\omega \times N_T} \times \sum_{j=1}^{N_T} \sum_{i=1}^{N_\omega} (X_{i,j} - M_j)(X_{i,j} - M_j)^{\mathrm{T}}$$

where $M_j = [m_j^1, ..., m_j^s]^{\mathrm{T}}$ is the mean vector of the s considered color texture features characterizing the learning images of the class T_j.

The measure of the class separability is defined by the between-class dispersion matrix Σ_S:

$$\Sigma_S = \frac{1}{N_T} \times \sum_{j=1}^{N_T} (M_j - M)(M_j - M)^{\mathrm{T}}$$

where $M = [m^1, ..., m^s]^{\mathrm{T}}$ is the mean vector of the s color texture features for all the classes.

The most discriminating feature space maximizes the information criterion :

$$J_s = \mathrm{trace}\Big((\Sigma_C + \Sigma_S)^{-1} \Sigma_S\Big)$$

At each step of the sequential selection procedure, a feature is added and the dimension d of the selected feature space increases. Therefore, for different quantization levels, it seems interesting to study the influence of d on the classification results and on the computation time.

C. Classification

During the classification stage, we propose to classify the test images thanks to the nearest neighbor classifier which is a simple and widely used classifier. This classifier operates in the selected d-dimensional feature space.

V. Experimental results

In this section, we present the classification results obtained by applying the proposed method on two well-known and largely used benchmark color texture databases presented in subsection V-A. In the next subsection, we study the influence of the RSCCM processing time on the computation time required to extract a color texture feature and subsection V-C shows the influence of the dimension of the selected feature space on the performance of classification.

A. VisTex and OuTex databases

To examine the influence of the use of RSCCMs on the processing time and on the quality of texture classification, experimental results are achieved by using two different benchmark texture sets, coming from the VisTex and the OuTex databases, respectively [14], [16]. These sets are available at the OuTex web site[1] as test suite Contrib-TC-00006 and Contrib-TC-00013, respectively [16]. We choose to use the same sets of color texture images as Arvis and Mäenpää do [7], [17]. To build these sets, 54 VisTex textures and 68 Outex ones are split up into sub-images whose size is 128×128 pixels. Since the original image size is 512×512 for the VisTex textures, and 746×538 for the Outex ones, this makes a total of 16 sub-images per texture and 20 sub-images per texture, respectively. These sub-images are then split up into learning and testing databases according to the Holdout method: half of the samples for each texture are used to build the learning image database, while the other samples are used to test the performance reached by the classification method.

[1] http://www.outex.oulu.fi/temp/

B. RSCCM and color texture feature computation time

Figure 6 displays the mean computation time Te required for extracting an Haralick feature, from an OuTex image whose size is 128×128 pixels, according to the quantization level Q used to compute RSCCM. These times, given in millisecond, are measured with an implementation on a PC cadenced at 2.08 GHz with 448 Mo of RAM.

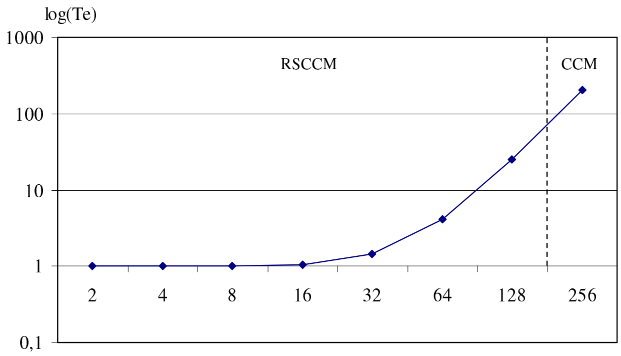


Fig. 6. Mean computation time Te (in millisecond) required to extract a feature, from an OuTex image whose size is 128×128 pixels, according to the quantization level Q.

Figure 6 shows that the quantization level has a significant influence on the feature extraction time, especially when Q is higher than 32. So, the use of RSCCMs largely reduces the computation time of a color texture feature, compared with that required to extract features from classical CCMs.

C. Number of selected features and classification results

Figures 7 and 8 illustrate the classification results obtained by our approach applied to VisTex and OuTex color texture image databases, respectively. These figures show, for different quantization levels, the rates of well-classified test images, with respect to the dimension d of the feature space built by our sequential selection procedure.

We can notice that when Q is higher than or equal to 16, the color quantization does not significantly influence the rates of well-classified images. When d is higher than or equal to 10, the obtained classification rates are quite similar to those obtained when the level Q ranges from 4 to 256.

The best classification results reaches 98.6% when Q is set to 64 and d is set to 19 for the VisTex image set and 95.3% with Q is set to 64 and d is set to 19 for the OuTex ones. These results show the efficiency of the proposed method because the best classification results, which have been yet obtained, reach 100% with the VisTex database and 95.4% with the OuTex one [17].

Finally, it is interesting to evaluate the processing time of the learning and classification stages. The learning stage is divided into two steps: the feature extraction step and the feature selection step. By examining Table I, we compare the processing times required by the two steps of the feature extraction stage when Q is set to 64 (RSCCM) and 256 (CCM). Thanks to RSCCM, the processing time is reduced with 97.8%, when d is set to 19. Likewise, the classification stage is divided into two steps: the feature extraction and the classification steps. Table II shows that when d is set to 19, the processing time is reduced with 73.8% when Q is equal to 64 (RSCCM), compared to Q set to 256 (CCM). Obviously, these times depend on the used classification algorithm (here the 1-Nearest Neighbor).

These examples illustrate how RSCCM associated with a feature selection procedure largely decreases the computation time of feature extraction performed during the learning and classification stages.

VI. Conclusion

In this paper, we have presented a feature selection scheme which builds a low-dimensional feature space for texture classification. For this purpose, we have introduced the Reduced-Size CCMs (RSCCMs) which result from color quantization. We have shown that the analysis of Haralick features extracted from these RSCCMs provides satisfying classification results while significantly reducing the processing time. The originality of the proposed approach is to extract color texture features not only from images coded in a single color space but from images coded in several color spaces in order to take advantage of each of them and to improve the classification results.

In this framework, the results presented in this paper show that the automatic selection of Haralick features extracted from RSCCMs is a relevant and efficient tool to classify color textures coded in different color spaces.

However, perspectives on three points merit to be studied. First, RSCMMs are deduced from color quantization. It would be interesting to study the influence of the procedure used to perform the color quantization on the quality of RSCMM. Then, the number of selected features is set by the user since no efficient stopping criterion of the sequential selection procedure is available. We presently work on a new strategy in order to determine the final dimension of the selected feature space. Finally, the feature selection is based on a supervised learning which requires a high number of prototypes to well define the classes. When we do not dispose of a sufficient number of prototypes, such a procedure does not perform good results. So, a semi-supervised learning scheme should be developed for color texture feature selection.

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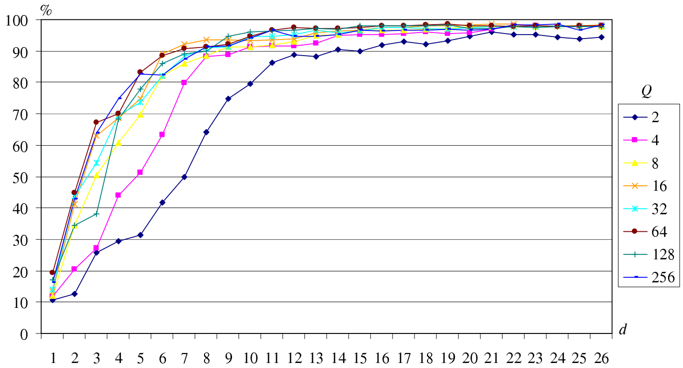

Fig. 7. Well classification rates obtained by our approach applied to VisTex test images according to the dimension d of the selected feature space, for different quantization levels Q.

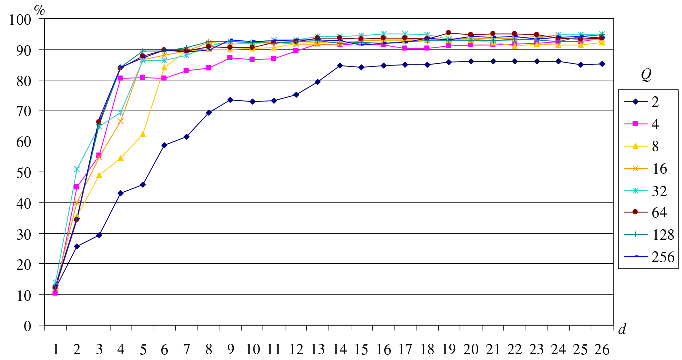

Fig. 8. Well classification rates obtained by our approach applied to OuTex test images according to the dimension d of the selected feature space, for different quantization levels Q.

TABLE I
PROCESSING TIME OF THE LEARNING STAGE.

	Learning stage (for 68x10 learning images whose size is 128x128 pixels)		
	Feature extraction (2352)	Feature selection (d 19)	**Total**
Q 64	6 167 720 ms	79 703 ms	**2 2 ms**
Q 256	287 216 000 ms	79 703 ms	**28 2 ms**

TABLE II
PROCESSING TIME OF THE CLASSIFICATION STAGE.

	Classification stage (for an image whose size is 128x128 pixels)		
	Feature extraction (d 19)	Classification	**Total**
Q 64	79 ms	1 506 ms	**8 ms**
Q 256	4 535 ms	1 506 ms	**ms**

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