



HAL
open science

A new benchmark image test suite for evaluating color texture classification schemes

Alice Porebski, Nicolas Vandembroucke, Ludovic Macaire, Denis Hamad

► **To cite this version:**

Alice Porebski, Nicolas Vandembroucke, Ludovic Macaire, Denis Hamad. A new benchmark image test suite for evaluating color texture classification schemes. *Multimedia Tools and Applications*, 2014, 70 (1), pp.543-556. 10.1007/s11042-013-1418-8. hal-00794488

HAL Id: hal-00794488

<https://hal.science/hal-00794488>

Submitted on 16 Feb 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

A new benchmark image test suite for evaluating colour texture classification schemes

A. Porebski · N. Vandenbroucke · L. Macaire · D. Hamad

Received: date / Accepted: date

Abstract Several image test suites are available in the literature to evaluate the performance of classification schemes. In the framework of colour texture classification, OuTex-TC-00013 (OuTex) and Contrib-TC-00006 (VisTex) are often used. These colour texture image sets have allowed the accuracies reached by many classification schemes to be compared. However, by analysing the classification results obtained with these two sets of colour texture images, we have noticed that the use of colour histogram yields a higher rate of well-classified images compared to colour texture features. It does not take into account any texture information in the image, this incoherence leads us to question the relevance of these two benchmark colour texture sets for measuring the performances of colour texture classification algorithms. Indeed, the partitioning used to build these two sets consists of extracting training and validating sub-images of a original image. We show that such partitioning leads to biased classification results when it is combined with a classifier such as the nearest neighbour. In this paper a new relevant image test suite is proposed for evaluating colour texture classification schemes. The training and the validating sub-images come from different original images in order to ensure that the correlation of the colour texture images is minimized.

Keywords Benchmark colour texture test suite · Supervised classification · OuTex · VisTex

A. Porebski · N. Vandenbroucke · D. Hamad
Laboratoire LISIC - EA 4491 - Université du Littoral Côte d'Opale - Maison de la Recherche Blaise Pascal - 50, rue Ferdinand Buisson - BP 719 - 62228 Calais Cedex - FRANCE - Tel: +33 3 21 38 85 60 - Fax: +33 3 21 38 85 05 - E-mail: porebski@lisic.univ-littoral.fr

L. Macaire
Laboratoire LAGIS - UMR CNRS 8219 - Université Lille 1 - Sciences et Technologies - Cité Scientifique - Bâtiment P2 - 59655 Villeneuve d'Ascq - FRANCE

1 Introduction

Many studies of texture analysis have been carried out on grey-level images. Their extension to colour is still relatively recent and has led to a growing interest in the scientific community. The construction of several databases of colour texture images shows this interest and the requirement of common benchmark databases in order to test different texture analysis algorithms and to compare their performance. Four benchmark colour texture databases are commonly considered:

- The **VisTex** database is a collection of natural colour textures observed under non-controlled illumination conditions [1]. This database is composed of 168 images that are divided into 19 categories of colour texture. These images are available in different sizes. However, for each category of texture, only a limited number of samples are available. Indeed, the number of images per category ranges from 2 to 20. Most of the authors who have used this database to evaluate the performance of their classification scheme, have divided the images into several sub-images in order to increase the number of samples [2, 3, 4, 5, 6, 7].
- The **BarkTex** database includes six tree bark classes, with 68 images per class, available in two sizes [8]. Like VisTex, the images of the BarkTex database represent natural colour textures which have been acquired under non-controlled illumination conditions. However, although the number of object categories is lower, this database is much more complex than VisTex as all the BarkTex images represent a single type of object, namely bark of trees.
- The **OuTex** database has been created in order to provide a wide range of textures for image processing applications [9]. Like the VisTex database, OuTex contains a large number of different objects. They are divided into 29 categories of colour texture images and the number of images per category ranges from 1 to 47. Contrary to VisTex and BarkTex, the OuTex database provides images that are acquired under controlled conditions. Each image is available with different illuminants, resolutions and rotation angles. In a similar manner to the VisTex database many authors have overcome the limited number of samples by creating multiple sub-images [3, 4, 10, 11, 12].
- Contrary to the three previous databases, each class of the **Curet** database is defined by a single colour texture which has been observed with over 200 combinations of illumination and viewing directions [13]. This database is divided into 60 classes of colour texture images.

These databases have been used several times in the framework of supervised classification of images. To operate a supervised colour texture classification, it is necessary to extract training and validating image subsets from the database. The training subset is used to build a discriminating feature space during a supervised learning stage. For this purpose, the training images are first coded in one or several colour spaces [14]. Colour texture features are

then computed from the so-coded images. Each image is thus represented in a feature space in which a classifier operates during a decision stage to determine the class to which the image belongs. The validating subset is thus used to evaluate the performances of the proposed classification scheme during this decision stage [15]. Among the learning algorithms commonly used in the framework of colour texture classification, there are local algorithms, where classifiers like the k Nearest Neighbour (k -NN) are considered, and global algorithms, among which we find the Support Vector Machines (SVM) classifier [16].

Several approaches are commonly considered to build the training and the validating subsets, like the holdout decomposition [3,4,17,18] or like the leaving-one-out method [7,19,20,21].

Most of the authors who have assessed the efficiency of a colour texture classification algorithm, have considered image test suites extracted either from the VisTex or the OuTex databases [2,3,4,5,6,7,10,11,17,20,22]. Among these different sets, two have often been used in the literature: the OuTex-TC-00013 and Contrib-TC-00006 test suites¹. They have allowed the classification performances reached by several features, like 3D colour histogram [3,4,23], Haralick features [11,24], Local Binary Pattern (LBP) histogram [4,10], features from autoregressive models [23] or from wavelet transform [12] to be evaluated using one or several colour spaces. Several studies where colour texture classification algorithms have been applied on the OuTex-TC-00013 and Contrib-TC-00006 test suites are presented in tables 1 and 2.

Using the same test suites for evaluating different classification algorithms allows the performance of these algorithms to be compared. However, by analysing and comparing the classification results obtained with these two sets of colour texture images, we have noticed some incoherences. That leads us to reassess the relevance of these two benchmark colour texture sets for measuring the performance of colour texture classification algorithms (see section 2). Indeed, the partitioning which builds a training and a validating subset from an initial image set can lead to biased classification results, when it is combined with a classifier such as the nearest neighbour classifier. In section 3 a new colour texture test suite based on an alternative partitioning is proposed and its relevance is evaluated in section 4.

2 Limits of the OuTex-TC-00013 and Contrib-TC-00006 test suites

In this section, we first describe the OuTex-TC-00013 and Contrib-TC-00006 test suites (see section 2.1) and we then synthesize the classification results obtained by the different authors with these two benchmarks sets (see section 2.2). Finally, we highlight the incoherences related to the building of these two

¹ <http://www.OuTex.oulu.fi/temp/>

sets (see section 2.3) and corroborate our analysis using experimental data (see section 2.4).

2.1 The OuTex and VisTex colour texture sets

2.1.1 *OuTex set: OuTex-TC-00013*

The OuTex set is available at the OuTex web site as test suite OuTex-TC-00013. To build this set, 68 colour texture images of the OuTex database, whose size is 746×538 pixels, are split up into 20 disjoint sub-images whose size is 128×128 pixels [4]. Let us note that several of these colour texture images come from the same category of colour textures but each of the 68 images define one class of colour texture. Here, the 20 sub-images of a same class come from the same acquired image. Figure 1 shows an example of OuTex colour textures among the 68 available. The images of the considered OuTex set have been acquired with a 100 dpi resolution at 0° rotation and with the 2856 K incandescent CIE A light source.

Among the 1360 images of the OuTex set, 680 images are used to build the training subset and the 680 remaining ones to build the validating subset, according to the holdout decomposition method.

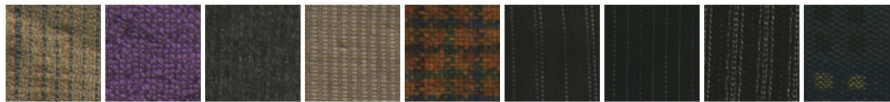


Fig. 1 Example of OuTex colour textures among the 68 available ones: each image illustrates a class of texture.

2.1.2 *VisTex set: Contrib-TC-00006*

The VisTex set is available at the OuTex web site as test suite Contrib-TC-00006. To build this set, 54 colour texture images (see figure 2), whose size is 512×512 pixels, are split up into 16 disjoint sub-images whose size is 128×128 pixels [4]. So, the 16 sub-images of a same class come from the same acquired image.

Among the 864 images of the VisTex set, 432 images are used to build the training subset and the 432 remaining images are used to build the validating subset, according to the holdout decomposition.



Fig. 2 Example of VisTex colour textures among the 54 available ones: each image illustrates a class of texture.

After having described the OuTex and VisTex sets, the next section synthesizes the classification results obtained by the authors who have assessed the efficiency of their colour texture classification schemes using these two sets.

2.2 Analysis of the classification results

Tables 1 and 2 show the different classification rates reached with the OuTex and VisTex validating subsets, respectively. The first column of these tables indicates the references of the authors who have applied their colour texture classification schemes on the OuTex or VisTex set. The second presents the colour spaces that have been used to code the colours within the images [14]. The texture features which have been processed from the colour images, are shown in the third column. Finally, the last column presents the rate T (%) of well-classified validating images obtained with the classifier defined in the fourth column. These rates are sorted in descending order.

Table 1 Comparison between the well-classified image rates (T) reached with the OuTex validating subset.

Ref.	Colour space	Features	Classifier	T (%)
[14]	Multi colour spaces	Haralick features from RSCCMs ²	1-NN	96.6
[4]	<i>HSV</i>	3D colour histogram	1-NN	95.4
[11]	<i>RGB</i>	Haralick features from RSCCMs	5-NN	94.9
[3]	<i>RGB</i>	3D colour histogram	3-NN	94.7
[23]	Improved- <i>HLS</i>	3D colour histogram	1-NN	94.5
[10]	<i>HSV</i>	Between and within LBP histogram	SVM	93.5
[4]	<i>RGB</i>	Between colour component LBP histogram	1-NN	92.5
[23]	Improved- <i>HLS</i>	Features from autoregressive models + 3D colour histogram	1-NN	88.9
[23]	<i>Lab</i>	Features from autoregressive models	1-NN	88.0
[4]	<i>RGB</i>	Within colour component LBP histogram	1-NN	87.8
[12]	<i>RGB</i>	Features from wavelet transform	7-NN	85.2
[25]	<i>Lab</i>	Morphological covariance	1-NN	80.1

Table 2 Comparison between the well-classified image rates (T) reached with the VisTex validating subset.

Ref.	Colour space	Features	Classifier	T (%)
[4]	$I_1I_2I_3$	3D colour histogram	1-NN	100
[4]	Lab	Within colour component LBP histogram	1-NN	100
[14]	Multi colour spaces	Haralick features from RSCCMs	1-NN	99.8
[3]	$I_1I_2I_3$	3D colour histogram	3-NN	99.8
[10]	RGB	Between and within LBP histogram	SVM	99.8
[4]	RGB	Between colour component LBP histogram	1-NN	99.5
[11]	RGB	Haralick features from RSCCMs	5-NN	97.7

By analysing these tables, we notice that the classification accuracies reached with the different classification schemes are relatively close to each other, particularly for the VisTex colour texture set. We also notice that, among the twelve classification algorithms which have been tested on the OuTex set, eight perform the first nearest neighbour (1-NN) classifier. Likewise, more than half of the classification algorithms which have been tested on the VisTex set consider the 1-NN classifier. Furthermore, for these two image test suites, we notice that very high classification accuracies are obtained with 3D colour histogram. However, it only characterizes the colour distribution within the colour space and does not take into account the spatial relationships between neighbouring pixels, as a colour texture feature should. To understand this result, let us examine the OuTex and VisTex sets.

2.3 Discussion about the OuTex and VisTex sets

According to the holdout decomposition, the OuTex and VisTex sets are divided into two subsets: the training and the validating subsets. The sub-images which constitute these two subsets, come from the same original image of colour texture according to the partitioning presented in figure 3.

This figure, based on an image of the OuTex database, shows that ten sub-images extracted from the original colour texture image constitute a part of the training subset, while the ten others are validating images. As the sub-images of the training and the validating subsets come from the same original colour texture image, they are very similar. So, the points which characterize

² Reduced Size Chromatic Co-occurrence Matrices

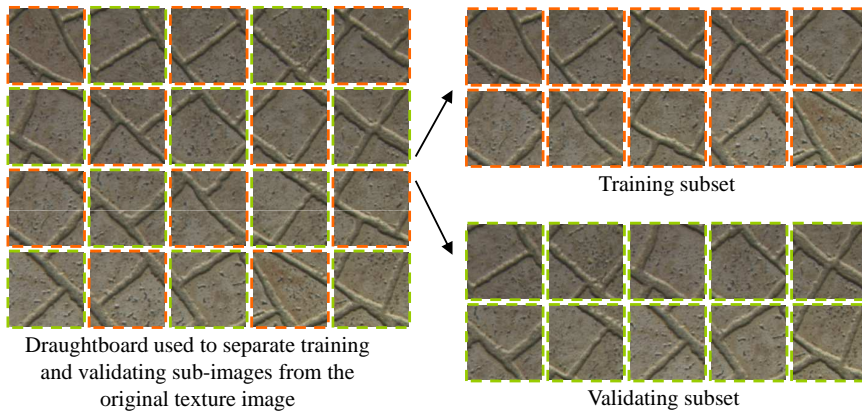


Fig. 3 Building of the training and the validating subsets according to a draughtboard partitioning.

these colour texture sub-images in the feature space would be very close to each other, whatever the considered feature space.

According to the considered classifier, this partitioning could provide high classification accuracy whatever the considered features. With a local learning algorithm such as the 1-NN classifier, the probability to assign sub-images coming from the same original image to a same class is very high, because at least one training sub-image is spatially close to any validating sub-image [16].

2.4 Experiments

In order to show that the partitioning presented in figure 3 provides biased classification results when it is combined with a specific classifier, the classification results reached with a classifier based on a local learning and a classifier based on a global learning are compared. For this purpose we consider the 1-NN classifier and the rank sum classifier, which considers more than the single nearest training sub-image to classify the validating sub-images.

The rank sum classifier first computes the distances between each validating image and all training images in the feature space and then ranks the obtained measures in ascending order. For each class, the rank sum of its training images is computed. The validating image is finally assigned to the class for which the rank sum is the lowest. To make the decision, the classifier takes into account all the training images, and even possible outliers like training sub-images which are spatially far from the validating sub-image to be classified. So high accuracy is more difficult to obtain with the rank sum classifier than with the 1-NN one. The rates of images that are well-classified by the rank sum thus indicate more precisely the discriminating power of the examined feature spaces.

Tables 3 and 4 show the classification accuracies reached by the 1-NN and the rank sum classifier, for three different sets of features:

- First we consider 3D colour histograms, which do not take into account the spatial relationships between neighbouring pixels, as a colour texture feature should. As Mäenpää *et al.* do in [4], we use the histogram intersection measure, that sums up the minimum values of two histograms for each histogram bin, to compare the training and the validating images. We also extract these histograms from colour texture images coded in the *HSV* colour space with a number of levels used to quantify the colour components set to 16 for the OuTex set and from images coded in the $I_1I_2I_3$ colour space with a quantization level set to 32 for the VisTex set.
- Then we consider Haralick features extracted from Reduced Size Chromatic Co-occurrence Matrices (RSCCMs). These features take into account both the colour distribution in a colour space and the spatial relationships between neighbouring pixels [24]. The aim is to compare the classification results obtained by the previous feature set composed of 3D colour histograms with those obtained by considering colour texture features. We propose to test two different approaches with these Haralick colour texture features:
 - To build the second feature set considered in our experiments, Haralick features are extracted from RSCCMs calculated in images coded in the *HSV* colour space for the OuTex set and from the $I_1I_2I_3$ space for the VisTex set, as Mäenpää *et al.* did with the 3D colour histograms [14].
 - Furthermore, we also propose to compute Haralick features extracted from RSCCMs calculated in several different colour spaces. To build the third colour texture feature set, a reduced number of discriminating features is selected thanks to a sequential selection procedure associated with criteria of class separability and compactness (see [14] for more details about the feature selection procedure). This approach is called the Multi colour Space Feature Selection (MCSFS) [24].

Table 3 Classification rates (T) reached by the 1-NN and the rank sum classifiers, for the OuTex validating subset.

colour spaces	Features	T (%) with 1-NN	T (%) with rank sum
Multi colour spaces	Haralick features from RSCCMs (MCSFS)	96.6	90.3
<i>HSV</i>	Haralick features from RSCCMs	92.5	82.5
<i>HSV</i>	3D colour histogram	95.4	80.7

Table 4 Classification rates (T) reached by the 1-NN and the rank sum classifiers, for the VisTex validating subset.

colour spaces	Features	T (%) with 1-NN	T (%) with rank sum
Multi colour spaces	Haralick features from RSCCMs (MCSFS)	99.8	95.1
$I_1 I_2 I_3$	Haralick features from RSCCMs	98.6	91.9
$I_1 I_2 I_3$	3D colour histogram	100	82.4

By analysing tables 3 and 4, we first notice that the rates of well-classified images obtained by the three tested approaches are close when the 1-NN classifier operates, whereas they are scattered when the rank sum classifier is used. Indeed, the difference between the results provided by the MCSFS approach and those obtained by analysing 3D colour histograms is rather low (about 1%) when the 1-NN classifier is considered, whereas the results are more dispersed for the rank sum classifier (the difference reaches 9.6% for the OuTex set and 12.7% for the VisTex set).

We also note that, with the rank sum classifier, the best rate of well-classified images is obtained with MCSFS (90.3% for the OuTex set and 95.1% for the VisTex set), whereas the lowest accuracy is obtained with the 3D colour histogram which does not take into account any texture information (80.7% for the OuTex set and 82.4% for the VisTex set).

These experiments thus corroborate the previous analysis (section 2.3) which shows that, by considering the partitioning presented in figure 3, the use of a 1-NN classifier provides biased classification results. They allow us to conclude that with such partitioning, a classifier based on a global learning algorithm, like the rank sum or the SVM classifier, allows to better evaluate the relevance of the consider features. Iakovidis et al. consider a nonlinear SVM classifier based on a global learning algorithm and overcome the problem of such partitioning [10].

In order to be compatible with all the classifiers, a partitioning must extract the training and the validating sub-images from different original images, like for object recognition applications. It ensures that colour texture images of the training and the validating subsets are not as strongly correlated. Such a partitioning should be more consistent in the context of industrial applications, where the training images are different from the images that are classified on-line. In the next section, we propose to build a new benchmark colour texture test suite that overcomes this problem.

3 New benchmark colour texture image test suite

In order to build a colour texture set for which training and validating sub-images come from different original images, we have to dispose of several original images for each class. The number of images by category for the OuTex and VisTex databases is too few if we want to consider all the categories of these databases. We thus propose to build a new colour texture image test suite coming from the BarkTex database. This database, which has been used by several authors [5, 19, 21, 26], is composed of six tree bark classes, with 68 images per class [8]. Figure 4 shows an example of BarkTex colour textures.

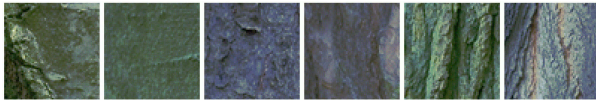


Fig. 4 Example of BarkTex colour textures: each image illustrates a class of texture.

The size of the images that we use to build the new set, is 256×384 pixels. A region of interest, centered on the bark and whose size is 128×128 pixels, is first defined. Then, four sub-images whose size is 64×64 pixels are extracted from each region. We thus obtain a set of $68 \times 4 = 272$ sub-images per class. Among the 1632 resulting images, 816 images are used for the training subset and the 816 others are considered as validating images.

In order to ensure that colour texture images are as weakly correlated as possible, we extract training and validating sub-images from different original images thanks to the partitioning 1 presented in figure 5. Here, the four sub-images extracted from a same original image belong either to the training or the validating subset. This new BarkTex image test suite can be downloaded on the web at https://www-lisic.univ-littoral.fr/~porebski/BarkTex_image_test_suite.html.

4 Experimental results

Table 5 shows the classification accuracies reached by the 1-NN and the rank sum classifiers with the new BarkTex benchmark image test suite. We consider the same features as in section 2.4.

By analysing the results presented in table 5, we notice that there is a significant difference (about 14%) between the results provided by the MCSFS approach (75.9%) and those obtained by analysing 3D colour histograms (61.6% with the HSV colour space and 62.9% with the $I_1 I_2 I_3$ colour space) when the nearest neighbour classifier is performed. This difference is similar with the rank sum classifier (approximately 12.5%).

This result contrasts with those obtained with the OuTex and VisTex sets, where the rates of well-classified images obtained by the different tested ap-

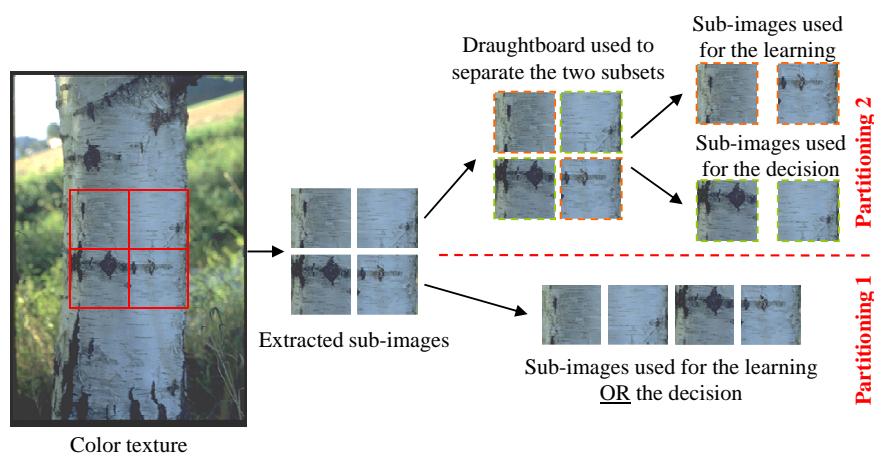


Fig. 5 Building of the training and the validating subsets thanks to **partitioning 1** and **partitioning 2**.

Table 5 Comparison between the well-classified image rates (T) reached by the 1-NN and the rank sum classifiers with the new BarkTex validating subset (partitioning 1).

colour spaces	Features	T (%) with 1-NN	T (%) with rank sum
Multi colour spaces	Haralick features from RSCCMs (MCSFS)	75.9	62.1
HSV	Haralick features from RSCCMs	73.3	51.3
$I_1 I_2 I_3$	Haralick features from RSCCMs	62.6	50.2
HSV	3D colour histogram	61.6	51.0
$I_1 I_2 I_3$	3D colour histogram	62.9	48.3

proaches are always close when the 1-NN classifier operates with the draughtboard of figure 3.

With the new BarkTex benchmark image test suite, the colour texture features most often allow to obtain better classification results than features which do not take into account the spatial relationships between pixels in the image. So, the partitioning 1 scheme provides a realistic measure of feature relevance.

In order to show that it is the partitioning which, when it is combined with the 1-NN classifier, provides high classification accuracy whatever the considered features, we have compared two partitioning strategies.

The first partitioning, called **partitioning 1** and described in figure 5, allows to build the new benchmark colour texture image test suite. Here, the four sub-images extracted from a same original image belong either to the training or the validating subset.

The second partitioning consists of extracting training and validating sub-images from the same original images, as for the OuTex and the VisTex sets (see figure 5). This partitioning, called **partitioning 2**, has been proposed by Münzenmayer and *al.* [21].

Table 6 shows the classification rates obtained with the image set built thanks to the partitioning 2 and the Holdout decomposition. It confirms the conclusions obtained with the OuTex and VisTex sets. When images of the training and validating subsets come from the same original images, the best classification result (95.3%) is obtained with 3D colour histogram although it only characterizes the colour distribution within the colour space and the colour representation between the different classes of the new BarkTex set is rather uniform. Furthermore, the difference between the results provided by the MCSFS approach which considers colour texture features and those obtained by analysing 3D colour histograms is rather low (about 1.3%) when the 1-NN classifier is used. On the contrary, the classification results are much scattered when the rank sum classifier operates (the difference is about 12.8%). These experiments thus confirm that, with the partitioning 2, the classification accuracies are biased when a classifier such as 1-NN is used. So, it is necessary to dispose of a colour texture set where the training and the validating sub-images come from different original images.

Table 6 Comparison between the well-classified image rates (T) reached with the partitioning 2.

colour spaces	Features	T (%) with 1-NN	T (%) with rank sum
Multi colour spaces	Haralick features from RSCCMs (MCSFS)	93.5	62.7
HSV	Haralick features from RSCCMs	93.4	56.1
$I_1 I_2 I_3$	Haralick features from RSCCMs	79.0	54.0
HSV	3D colour histogram	95.3	51.2
$I_1 I_2 I_3$	3D colour histogram	89.1	48.7

5 Conclusion

Most of the authors who want to assess the relevance of their colour texture classification algorithms, have considered the OuTex-TC-00013 and Contrib-TC-00006 test suites. However, by analysing the classification results obtained by a 1-NN classifier with these two sets of colour texture images, we have noticed that colour histogram allows to obtain a higher rate of well-classified images compared to colour texture features, although it does not take into account any texture information in the image.

This incoherence leads us to question the relevance of the two benchmark colour texture test suites OuTex-TC-00013 and Contrib-TC-00006 for measuring the performances of colour texture classification algorithms. The partitioning used to build these two sets consists of extracting training and validating sub-images from a same original image. We have shown that such partitioning, when it is combined with a classifier based on a local learning algorithm such as 1-NN, leads to biased classification results. This analysis is confirmed by experimental data obtained with another classifier and another way of partitioning the original images into training and validating sub-images.

These experiments allow us to conclude that with such partitioning, a classifier based on a global learning algorithm like the rank sum or the SVM classifier should be used. We have also proposed a new relevant image test suite for evaluating colour texture classification schemes, where the training and the validating sub-images come from different original images in order to ensure a minimum degree of correlation between colour texture images and a compatibility with all the classifiers.

This paper highlights the requirement of relevant benchmark colour texture databases and proposes a first solution. On the basis of this work, other test suites should be created in order to efficiently test the performances of colour texture classification methods.

References

1. R. Picard, C. Graczyk, S. Mann, J. Wachman, L. Picard, and L. Campbell, "Vision texture database," Media Laboratory, Massachusetts Institute of Technology (MIT), Cambridge, <http://vismod.media.mit.edu/pub/VisTex/VisTex.tar.gz>.
2. A. Drimbarean and P.F. Whelan, "Experiments in colour texture analysis," *Pattern Recognition Letters*, vol. 22, no. 10, pp. 1161–1167, 2001.
3. M. Pietikäinen, T. Mäenpää, and J. Viertola, "Color texture classification with color histograms and local binary patterns," in *Proceedings of the 2nd International Workshop on Texture Analysis and Synthesis*, 2002, pp. 109–112.
4. T. Mäenpää and M. Pietikäinen, "Classification with color and texture: jointly or separately?," *Pattern Recognition Letters*, vol. 37, no. 8, pp. 1629–1640, 2004.
5. C. Palm, "Color texture classification by integrative co-occurrence matrices," *Pattern Recognition Letters*, vol. 37, no. 5, pp. 965–976, 2004.
6. O.J. Hernandez, J. Cook, M. Griffin, C. De Rama, and M. McGovern, "Classification of color textures with random field models and neural networks," *Journal of Computer Science & Technology*, vol. 5, no. 3, pp. 150–157, 2005.
7. A. Khotanzad and O.J. Hernandez, "A classification methodology for color textures using multispectral random field mathematical models," *Mathematical and Computational Applications*, vol. 11, no. 2, pp. 111–120, 2006.

8. R. Lakmann, "Barktex benchmark database of color textured images," 1998, Koblenz-Landau University, <ftp://ftphost.uni-koblenz.de/outgoing/vision/Lakmann/Bark-TeX>.
9. T. Ojala, T. Mäenpää, M. Pietikäinen, J. Viertola, J. Kyllönen, and S. Huovinen, "Outex new framework for empirical evaluation of texture analysis algorithms," in *Proceedings of the 16th International Conference on Pattern Recognition*, Quebec, Canada, 2002, vol. 1, pp. 701–706.
10. D. Iakovidis, D. Maroulis, and S. Karkanis, "A comparative study of color-texture image features," in *Proceedings of the 12th International Workshop on Systems, Signals & Image Processing (IWSSIP'05)*, Chalkida, Greece, 2005, pp. 203–207.
11. V. Arvis, C. Debain, M. Berducat, and A. Benassi, "Generalization of the cooccurrence matrix for colour images: application to colour texture classification," *Image Analysis and Stereology*, vol. 23, pp. 63–72, 2004.
12. Q. Xu, J. Yang, and S. Ding, "Color texture analysis using the wavelet-based hidden markov model," *Pattern Recognition Letters*, vol. 26, pp. 1710–1719, 2005.
13. K.J. Dana, B.V. Ginneken, S.K. Nayar, and J.J. Koenderink, "Reflectance and Texture of Real World Surfaces," in *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, San Juan, Puerto Rico, June 1997, pp. 151–157.
14. A. Porebski, N. Vandenbroucke, and L. Macaire, "Supervised texture classification: color space or texture feature selection?," *Pattern Analysis and Applications*, vol. 16, no. 1, pp. 1–18, 2013, doi:10.1007/s10044-012-0291-9.
15. N. Vandenbroucke, O. Alata, C. Lecomte, A. Porebski, and I. Qazi, *Color texture attributes*, chapter 6, Digital Color Imaging, ISTE Ltd/John Wiley & Sons, 2012.
16. R. Hable, "Universal consistency of localized versions of regularized kernel methods," *Journal of Machine Learning Research*, vol. 14, pp. 153–186, 2013.
17. P.S. Hiremath, S. Shivashankar, and J. Pujari, "Wavelet based features for color texture classification with application to CBIR," *International Journal of Computer Science and Network Security (IJCSNS)*, vol. 6, no. 9, pp. 124–133, 2006.
18. C. Münzenmayer, S. Wilharm, J. Hornegger, and T. Wittenberg, "Illumination invariant color texture analysis based on sum- and difference-histograms," in *Proceedings of the DAGM-Symposium*. 2005, pp. 17–24, Editions Springer-Verlag.
19. C. Palm and T.M. Lehmann, "Classification of color textures by gabor filtering," *Machine Graphics & Vision International Journal*, vol. 11, no. 2, pp. 195–219, 2002.
20. G. Van de Wouwer, P. Scheunders, S. Livens, and D. Van Dyck, "Wavelet correlation signatures for color texture characterization," *Pattern Recognition*, vol. 32, pp. 443–451, 1999.
21. C. Münzenmayer, H. Volk, C. Küblbeck, K. Spinnler, and T. Wittenberg, "Multispectral texture analysis using interplane sum- and difference-histograms," in *Proceedings of the DAGM-Symposium*. 2002, pp. 42–49, Editions Springer-Verlag.
22. E.L. Van Den Broek and E.M. Van Rikxoort, "Evaluation of color representation for texture analysis," in *Proceedings of the Belgium-Dutch Conference on Artificial Intelligence*, Groningen, The Netherlands, 2004, pp. 35–42.
23. I.U.H. Qazi, O. Alata, J.C. Burie, A. Moussa, and C. Fernandez-Maloigne, "Choice of a pertinent color space for color texture characterization using parametric spectral analysis," *Pattern Recognition*, vol. 44, no. 1, pp. 16–31, 2011.
24. A. Porebski, N. Vandenbroucke, and L. Macaire, "Comparison of feature selection schemes for color texture classification," in *Proceedings of the 2nd IEEE international Workshops on Image Processing Theory, Tools and Applications*, Paris, France, 2010, pp. 32–37.
25. E. Aptoula and S. Lefvre, "A comparative study on multivariate mathematical morphology," *Pattern Recognition*, vol. 40, no. 11, pp. 2914–2929, 2007.
26. A. Porebski, N. Vandenbroucke, and L. Macaire, "Iterative feature selection for color texture classification," in *Proceedings of the IEEE International Conference on Image Processing*, San Antonio, USA, 2007, pp. 509–512.