



Image segmentation based on the integration of colour–texture descriptors—A review

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ABSTRACT

The adaptive integration of the colour and texture attributes in the development of complex image descriptors is one of the most investigated topics of research in computer vision. The substantial interest shown by the research community in colour–texture-based segmentation is mainly motivated by two factors. The first is related to the observation that the imaged objects are often described at perceptual level by distinctive colour and texture characteristics, while the second is motivated by the large spectrum of possible applications that can be addressed by the colour–texture integration in the segmentation process. Over the past three decades a substantial number of techniques in the field of colour–texture segmentation have been reported and it is the aim of this article to thoroughly evaluate and categorise the most relevant algorithms with respect to the modality behind the integration of these two fundamental image attributes. In this paper we also provide a detailed discussion about data collections, evaluation metrics and we review the performance attained by state of the art implementations. We conclude with a discussion that samples our views on the field of colour–texture image segmentation and this is complemented with an examination of the potential future directions of research.

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1. Introduction

The use of colour and texture information collectively has strong links with the human perception and in many practical scenarios the colour-alone or texture-alone image information is not sufficiently robust to accurately describe the image content. An example is provided by the segmentation of natural images that exhibit both colour and texture characteristics. This intuitive psychophysical observation prompted the computer vision researchers to investigate a large spectrum of mathematical models with the aim of sampling the local and global properties of these two fundamental image descriptors. Nonetheless, the robust integration of colour and texture attributes is far from a trivial objective and this is motivated, in part, by the difficulty in extracting precise colour and texture models that can locally adapt to the variations in the image content. In particular the segmentation of natural images proved to be a challenging task, since these images exhibit significant inhomogeneities in colour and texture and in addition they are often characterised by a high degree of complexity, randomness and irregularity. Moreover, the strength of texture and colour attributes

can vary considerably from image to image and complications added by the uneven illumination, image noise, perspective and scale distortions make the process of identifying the homogenous image regions extremely difficult. All these challenges attracted substantial interest from the vision researchers, as the robust integration of the colour and texture descriptors in the segmentation process has major implications in the development of higher-level image analysis tasks such as object recognition, scene understanding, image indexing and retrieval, etc.

Over the past three decades, the field of image segmentation based on the integration of colour and texture descriptors has developed extensively, peaking with an abundance of algorithms published between the years 2007 and 2009. It is useful to note that in the period covered between 1984 and 2009 more than 1000 papers have been published in the literature and this figure acknowledges the fact that colour–texture analysis has positioned itself as one of the most researched areas in the field of image processing and computer vision. The statistics that evaluate the number of algorithms published on the topic of colour–texture analysis in the last three years (2007–2009) clearly indicate that this field of research has reached maturity and, as a result, distinct patterns or categories of approaches that sample either the nature of the feature extraction process or the methodologies employed for feature integration can be identified. The aim of this paper is to analyse from a theoretical perspective the main directions of

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research in the field of colour–texture analysis and to review the concepts and strategies that have been investigated in the process of colour–texture integration with a view of attaining robust image segmentation. Although several surveys have addressed the evaluation of colour-alone [1–3] or texture-alone [4–9] segmentation algorithms, we are not aware of any work in the literature that was concerned with the systematic analysis of the concepts and methodologies that were employed in the development of colour–texture image segmentation algorithms. We would like to emphasise that in this review we are particularly concerned with the analysis and categorisation of the published works with respect to the integration of colour and texture information in the segmentation process, which, in our opinion, is the only logical approach that can lead to a meaningful insight into this important field of research. There are mainly two reasons that justify the adopted approach. Firstly, such analysis facilitates a precise categorisation of the published algorithm based on the principles behind data fusion (feature integration) process, which is the central issue in the development of colour–texture segmentation schemes, and secondly such line of investigation will further allow the identification of generic colour–texture integration patterns that are decoupled from the application context that is the prevalent characteristic of the colour and texture feature extraction techniques. Thus, the foremost objectives of this paper are: (a) to categorise the main trends in colour–texture integration, (b) to sample the application context of the proposed implementations (whenever such discussion is appropriate), (c) to discuss the evaluation metrics that are currently used to assess the performance of the segmentation techniques, (d) to review the publicly available data collections (image databases) and (e) to analyse the performance of well-established state of the art implementations. It is useful to note that this review is primarily concerned with the analysis of algorithms that have been designed for the segmentation of still digital images and we will indicate when the evaluated approaches have been applied to the segmentation of video data.

To provide a comprehensive insight into the work in the field of colour–texture segmentation, we analysed a substantial number of papers published in journals and conference proceedings. To broaden the scope of this paper, we will not restrict ourselves only to the technical assessment of the investigated algorithms, but we will also try to provide an ample discussion where the ideas that emerged in the field of colour–texture integration over

the past three decades are systematically categorised and we will examine the practical context of the investigated methods whenever such discussion is possible. Also, we will place an important emphasis on the quantitative evaluation of the state of the art implementations in the field of colour–texture analysis. In this regard, we will present the numerical results achieved by the analysed state of the art methods and we will indicate the conditions and the type of data used in the evaluation process.

In the following subsections we will present the timeline and the tendency of development of published research in the area of colour–texture segmentation and then we will briefly discuss and cite representative early works. In Section 2 we will review the main trends with respect to the modality employed to combine the colour and texture information in the segmentation process. In Section 3 we will provide a detailed discussion about evaluation metrics and data collections and we will assess the performance obtained by state of the art implementations when applied to image segmentation. Section 4 of the paper provides a discussion that samples our views on the field of colour–texture analysis.

1.1. Colour–texture segmentation: timeline and trend of growth

During the period 1984–2008 the research in the area of colour–texture segmentation has witnessed a substantial growth. To illustrate this fact we have generated a graph where the records of published research works in the field analysed in our paper are plotted for each year until the end of December 2008. In this process we searched the information provided by the Compendex [10], Inspec [10] and IEEEExplore [11] databases and we have collated the results into a graph that is depicted in Fig. 1. The year 2009 was not included in the diagram shown in Fig. 1. This is motivated by the fact that a substantial number of research papers published in the last months of the year 2009 are not yet available in these online public databases and as a result the statistics for this year would be incomplete. However, based on the information we collected so far, we expect that the total number of papers on colour–texture analysis that will appear in conference proceedings and journals by the end of the year 2009 to match or even exceed the records generated for the year 2008.

As illustrated in Fig. 1, the period covered between 1984 and 1992 witnessed a small number of contributions that addressed the topic of colour–texture analysis. Nonetheless, there are objective

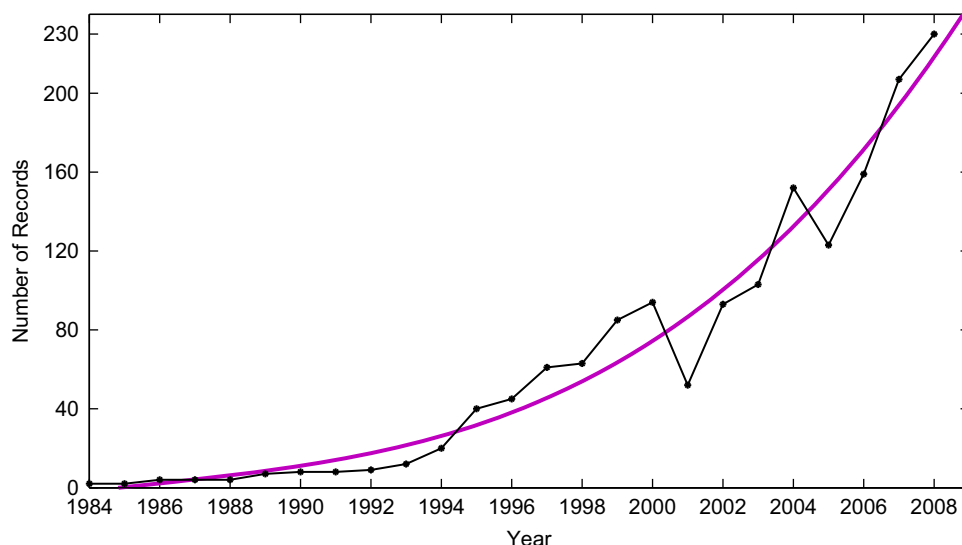


Fig. 1. The timeline and the number of the published research works on colour–texture segmentation from 1984 until 2008. These records were collected in November 2009.

factors that explain this relative small increase in research during the early years and this is primarily motivated by the technological limitations in computing and sensing devices. But with the proliferation of colour digital cameras and the widespread availability of modern computers, this area of research experienced a considerable interest from the computer vision community. This is clearly reflected by the substantial increase in the number of publications during the period 1993–2000. In the year 2001 we have noticed a small decrease in the number of published papers, but this trend was quickly reversed in the following years with the steepest growth being noticed between 2005 and 2008. To further illustrate the increased interest in the field of colour–texture analysis we have also plotted the trend line in Fig. 1 (see the thick solid line) that samples the rate of growth experienced in the period 1984–2008. The trend line clearly shows that this area of research has reached maturity and it is useful to note that the current studies in the field of colour–texture analysis are not only focused on theoretical advances related to feature extraction and integration but start to find a large spectrum of applications including medical imaging, image retrieval and indexing, image enhancement, pattern recognition, motion estimation, etc.

1.2. Early approaches (1984–1992)

Returning to the early years covered by the period between 1984 and 1992, in this section we will provide a short description of the first approaches that addressed the colour–texture segmentation. We have deliberately chosen to discuss the early works in the field of colour–texture segmentation at the beginning of the paper to allow the reader to sample the whole range of reasons that motivated the transition from the application domain that is characteristic for early colour–texture segmentation methods, to the algorithmic sophistication of the more recent approaches. This observation will become more apparent as we progress with the categorisation of the colour–texture segmentation algorithms in Section 2, where the most relevant directions of research are examined.

As indicated before, the early colour–texture segmentation approaches were developed in the context of a given application with the main focus being placed on the identification of the coherent regions in biomedical data. Some representative early papers include the work of Funakubo [12] where a region-based colour–texture segmentation method was introduced for the purpose of biomedical tissue segmentation and Harms et al. [13] where the colour information has been employed in the computation of texton values for blood cell analysis. Celenk and Smith [14] proposed an algorithm that integrates the spatial and spectral information for the segmentation of colour images detailing natural scenes, while Garbay discussed in [15] a number of methods that were developed for the segmentation of colour bone marrow cell images. Following the same feature integration principles, Katz et al. [16] introduced an algorithm for the automatic retina diagnosis where a combination of features including colour and edge patterns were employed to identify the vascular structures in the input image. One apparent limitation associated with these early colour–texture segmentation schemes resides in the lack of generality of the texture models that were used to sample the structural characteristics of the objects contained in digital images. Nonetheless substantial research efforts were devoted to answer this shortcoming and as a result the research community started to reassess the role of texture in the development of more generic colour–texture image analysis algorithms. Thus, texture analysis is explicitly addressed in [17], where the authors proposed to model “physically meaningful” textures such as foliage, grass, or road in outdoor scenes as a coloured Gaussian Markov Random Field (GMRF). However it is

useful to recall that most of the early approaches have been developed in the context of well-defined application domains and the integration of the colour and texture features has been approached in an opportunistic manner based on the strength of the features in the image. In this sense, Healey [18] includes the edge information to guide the colour segmentation process, while in [19] the authors combine the texture features extracted from each sub-band of the colour space with the colour features using heuristic merging rules. In [20], the authors discuss a method that employs the colour–texture information for the model-based coding of human images, while Shigenaga [21] adds the spatial-frequency texture features sampled by Gabor filters to complement the CIE Lab (CIE is the acronym for the Commission Internationale d’Eclairage) colour image information. In order to capture the colour–texture content, Rosenfeld et al. [22] calculated the absolute difference distributions of pixels in multi-band images, while Hild et al. [23] proposed a bottom-up segmentation framework where the colour and texture feature vectors were separately extracted and then combined for knowledge indexing.

From this short overview of early colour–texture analysis techniques we can conclude that although the majority of approaches were developed to address practical problems, a large spectrum of ideas and concepts were advanced in regard to issues related to feature extraction and feature integration. In particular it is useful to note that the main focus of the early works on colour–texture analysis was placed on feature extraction whereas studies on the complementary properties of the colour and texture attributes were less numerous. However, once the field of colour–texture analysis departed from the purely application driven context, the optimal integration of the colour and texture features started to be one of the main topics of research, a topic that continues to be an open research issue. Consequently, one important goal of our study is to review the work in the field of colour–texture segmentation based on the modality applied for feature integration and the representative directions of research will be examined in the next section of the paper.

2. Colour–texture segmentation: main directions of research

In this section we will present a comprehensive review of the existent colour–texture segmentation approaches based on the methodology behind their integration in the segmentation process. Each approach will be first described from a theoretical standpoint and then representative works belonging to each category will be summarised and discussed. Based on the approach used in the extraction and integration of the colour and texture features, we have identified three major trends in colour–texture analysis.

- (1) Implicit colour–texture feature integration [24–30,44]: the algorithms that belong to this category extract the texture features from single or multiple colour channels and the segmentation process is typically embedded into a coarse-to-fine strategy.
- (2) Approaches that extract colour and texture in succession, i.e. the segmentation task is formulated as a sequence of serial processes [31,33–40,45,46,50,51].
- (3) Approaches that extract the colour and texture features on separate channels and then combine them in the segmentation process. These approaches can be further sub-categorised with respect to the strategy employed in the feature integration step as follows:
 - (3.1) Region-based approaches that include: (a) split and merge [55–58]; (b) region growing [59,62–66] and (c) energy minimisation and active contours approaches [67–70,73,75,77].

- (3.2) Feature-based approaches that include statistical [78–86,88–90,92,95,97] and probabilistic segmentation schemes [98–102,105–113].

2.1. Implicit colour–texture integration

The main assumption behind approaches included in this category of colour–texture segmentation techniques is that the colour and texture are mutually dependent image attributes and their extraction should be accomplished from individual colour channels, from correlated pairs of colour channels or from the colour components that are combined into a vectorial representation.

In this regard, the algorithm proposed by Panjwani and Healey [24] is one of the representative works that belongs to this category. In their paper, the authors suggest a region-based approach that uses colour Gaussian Markov Random Field (GMRF) models which take into consideration not only the spatial interactions within each of the spectral bands but also the interactions between colour planes. The parameters of the GMRF are estimated using maximum likelihood methods and the segmentation algorithm is divided into two main steps. The first step of the algorithm performs region splitting that is applied to recursively divide the image into square regions until a uniformity criterion is upheld. The second step implements an agglomerative clustering which merges regions with similar characteristics in order to form texture boundaries. Experiments were performed on natural images and the authors conclude that the use of joint colour–texture models for unsupervised segmentation improves the segmented result when compared to colour-alone or texture-alone methods. Still they remark that the availability of *a priori* image knowledge would improve the effectiveness of the random field models when used in the context of unsupervised segmentation. A more detailed study that evaluated the importance of the chromatic content has been conducted by Paschos and Valavanis [25]. In this work the authors were mostly concerned with investigating the optimal approach to integrate the colour–texture features. The colour space used in their study is the xyY , where Y represents the luminance component that is separated from the chrominance values xy . The algorithm initially estimates a colour measure in a form of xy chromaticity maps and in the next step the combined colour–texture features are determined using the autocorrelation of the chromaticity maps that are calculated for orientations that span the 0 – 90° angle spectrum with a resolution of 5° . To produce a compact representation they define the global colour–texture descriptors as peaks in the directional histograms that are calculated for each orientation. The main aim of this paper was to emphasise the importance of the chromatic content when evaluated in conjunction with texture description but its main disadvantage is that it captures only the global colour–texture characteristics in the image, an information that may be useful in the implementation of image retrieval algorithms but too generic to be directly used in the construction of accurate segmentation schemes.

As opposed to the work by Paschos and Valavanis [25] where the feature integration has been approached from a conceptual

perspective, Shafarenko et al. [26] explored the practical problems associated with the implicit colour–texture integration by proposing a bottom-up segmentation approach that has been developed for the segmentation of randomly textured colour images. In this approach the segmentation process is implemented using a watershed transform that is applied to the image data converted to the CIE Luv colour representation. Nonetheless, the application of the watershed transform results in over-segmentation and to compensate for this problem the resulting regions are merged according to a colour contrast measure until a termination criterion is met. Although the authors assert that the proposed technique is completely automatic and returns accurate segmentation results, the experimental data indicates that the method has been specifically designed for processing granite and blob like images.

Hoang et al. [27] proposed a different approach to include the colour and texture information in the segmentation process and they applied the resulting algorithm to the segmentation of synthetic and natural images. Their approach proceeds with the conversion of the RGB image into a Gaussian colour model and this is followed by the extraction of the primary colour–texture features from each colour channel using a set of Gabor filters. Since the local colour–texture properties were sampled with a large number of filters, they applied Principal Component Analysis (PCA) to reduce the dimension of the feature space from sixty to four. The resulting feature vectors are used as inputs for a K -means algorithm that is employed to provide the initial segmentation that is further refined by a region-merging procedure. The main advantage of this algorithm resides in the application of the standard multi-band filtering approach to sample the local colour–texture attributes and the representation of the colour image in the wavelength Fourier space. Throughout their paper, the authors underline that the use of colour and texture features in combination provides far better discrimination than in cases when these features are individually used. Several segmentation results returned by the Hoang et al. [27] method when applied to a set of images from Berkeley database [52] are shown in Fig. 2. These results were obtained using the application made publicly available by the authors at the following web address: <http://staff.science.uva.nl/~mark/downloads.html#texture>.

A more involved colour–texture integration scheme (that is referred to as CTM—Compression-based Texture Merging) was proposed by Yang et al. [44]. In this approach the authors simultaneously extract the colour–texture features at pixel level by stacking the intensity values within a 7×7 window for each band of the CIE Lab converted image. As the segmentation is formulated as a data clustering process, for computational purposes the dimension of the colour–texture vectors is reduced to eight using Principal Component Analysis. The authors argue that often the colour–texture information cannot be described with normal distributions, and to compensate for this issue they employed a coding-based clustering algorithm which is able to accommodate input data defined by degenerate Gaussian mixtures. The proposed algorithm has been evaluated on images from Berkeley database and the authors were particularly interested in analysing the performance of the proposed segmentation



Fig. 2. Results obtained using the colour–texture segmentation algorithm proposed by Hoang et al. [27], when applied to a set of images sampled from Berkeley database [52]. For visualisation purposes, the borders between regions are superimposed on the original image.

technique when the internal parameters of the coding-based clustering technique were varied. Comparative results were reported when the CTM algorithm was evaluated against three state of the art implementations (mean-shift [41], Normalised Cuts [42] and Felzenszwalb and Huttenlocher (FH) [43]) and numerical results are provided in Table 3. A set of experimental results is depicted in Fig. 3 where the parameter γ that controls the coding data length is varied.

A conceptually related feature integration approach has been explored in the paper by Shi and Funt [28]. The major idea behind this approach is to provide a compact representation where the components of the RGB colour space are converted into a quaternion form that can be written as $q=R \cdot i+G \cdot j+B \cdot k$. The proposed algorithm consists of three computational stages. The first stage implements a training procedure where compressed feature vectors are generated by applying a Quaternion Principal Component Analysis (Q-PCA) to the training data obtained from a set of sub-windows taken from the input image. In the second step the input data is projected on the Q-PCA subspace and the resulting vectors are clustered using a K -means algorithm. To avoid issues related to over-segmentation, the final stage of the algorithm applies a merging process to join the adjacent regions with similar texture characteristics. The authors state that the use of a quaternion representation to sample the RGB colour–texture attributes is advantageous as both intra- and inter-channel relationships between neighbouring pixels are simultaneously taken into consideration. Although conceptually interesting, the performance of this colour–texture segmentation scheme is highly dependent on the appropriate selection of the size of the sub-windows that sample the local colour–texture content and also on several user-defined parameters such as the merge threshold and the number of clusters required by the K -means procedure. A similar idea has been employed by Wang et al. [29] where quaternion Gabor filters were proposed to sample the colour–texture properties in the image. In their approach the input image is initially converted to the Intensity Hue Saturation (IHS) colour space and then transformed into a reduced biquaternion representation. The segmentation task is implemented using a multi-stage process that includes the following computational steps: multi-channel Gabor filtering, feature space dimensionality reduction using Principal Component Analysis, K -Means clustering, mean-shift smoothing and post-processing refinements. The experiments were conducted using several images from the MIT VisTex database (Vision Texture—Massachusetts Institute of Technology) [76] and the

segmentation results were visually compared against those returned by JSEG (J-image SEGmentation) proposed by Deng and Manjunath [34].

Multi-scale implementations have been widely investigated in the context of texture analysis and due to their intrinsic advantages these approaches have been further generalised to cover the colour–texture domain. In this regard, we would like to draw attention to the paper by Jain and Healey [30] where a multi-scale classification scheme in the colour–texture domain has been investigated. In this work the authors applied a bank of circularly symmetric Gabor filters to extract unichrome and opponent image features that describe the local colour–texture information. Thus, the unichrome features capture the spatial structure of the texture and are independently extracted from each spectral band, while the opponent image features capture the spatial correlation between spectral bands in a multi-scale sense. The performance of the proposed algorithm was analysed in conjunction with classification tasks and the authors demonstrate that substantially improved results are obtained when both unichrome and opponent image features are used in the classification process, as opposed to situations when the primary features were analysed alone.

The implicit integration of colour and textural features was a characteristic of the early approaches in the field of colour–texture analysis and this observation is justified in part since texture analysis was predominantly evaluated in the context of greyscale images. Thus, the extension of the monochrome texture-based segmentation algorithms to colour data has been approached as the extraction of the texture features on each component of the colour representation and often the feature integration has been achieved using simplistic approaches. However the recent trend in colour–texture analysis departed from the principles behind implicit colour–texture feature extraction and more sophisticated models were adopted to attain improved segmentation accuracy.

2.2. Approaches that extract colour and texture in succession

To alleviate the limitations associated with the implicit integration of the colour–texture features in the segmentation process, alternative methodologies have been actively explored. Among various feature integration strategies, the evaluation of the colour and texture attributes in succession was one of the most popular directions of research. The main idea behind

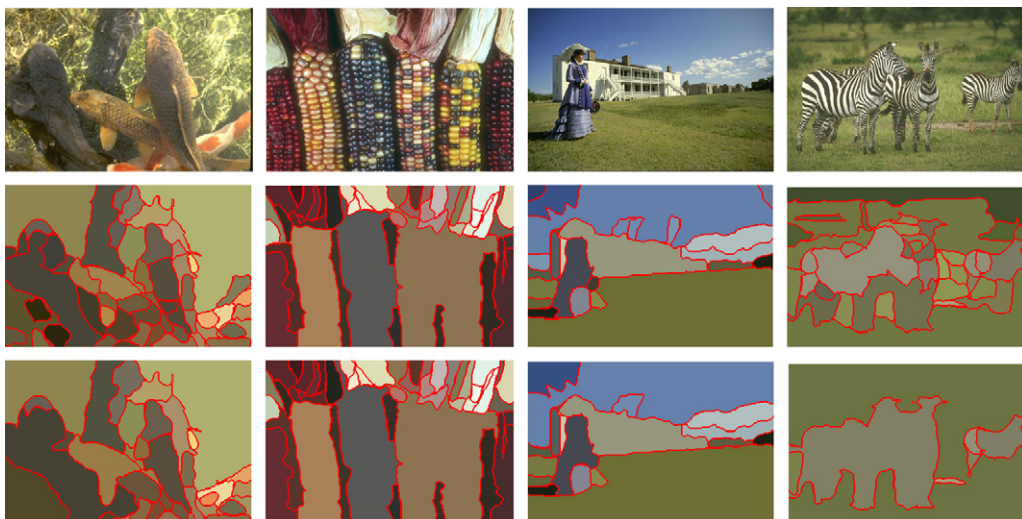


Fig. 3. 1st row: original colour–texture images from Berkeley database [52]; 2nd row: segmentation results obtained using the CTM (Compression-based Texture Merging) algorithm [44] when $\gamma=0.1$; 3rd row: segmentation results obtained using the CTM algorithm when $\gamma=0.2$.

approaches that belong to this category stems from the intuitive observation that there are not explicit rules (or analytical models) that fully describe the dependency between colour and texture during the image formation process and as a consequence their extraction should entail a serial process. Building on this concept, the image segmentation can be formulated as a multi-phase approach based on a coarse-to-fine image partitioning procedure. While this feature integration strategy proved quite successful when applied to practical scenarios, one of its major drawbacks is that it cannot be generalised since the features that are first extracted have the highest weight in the overall segmentation process. In addition, since the integration of the colour–texture features is performed in succession, there are limited algorithmic solutions that can be applied to compensate for the local inhomogeneities in colour distribution and to accommodate problems related to the complexity and irregularity of textural patterns that often occur in natural images. Also, it is worth mentioning that the colour–texture image segmentation schemes based on this feature integration approach involve the optimisation of a relative large number of parameters, a fact that limits their application to unsupervised segmentation tasks.

A representative segmentation algorithm that belongs to this category has been proposed by Mirmehdi and Petrou [31]. In this paper the authors introduced a colour–texture segmentation scheme where the feature integration is approached from a perceptual point of view. To accommodate local distortions in the colour–texture content the authors extract a multi-scale perceptual image tower that emulates the human perception when looking at the input image from different distances. In this process, convolution matrices are calculated using a weighted sum of Gaussian kernels and are applied to each colour plane of the opponent colour space $O_1O_2O_3$ (intensity, red–green and blue–yellow planes, respectively) to obtain the image data that make-up the perceptual tower. The result of this filtering process is used to characterise the texture present in the image in the multi-scale sense. The next stage of their approach deals with the extraction of the core colour clusters and the subsequent segmentation task is defined as a probabilistic process that hierarchically reassigns the non-core pixels starting from the coarsest image in the tower to the image with the highest resolution. This stage is performed after the input colour image is converted to the perceptually uniform CIE Luv colour space. The experiments were conducted using a number of colour–texture images and the evaluation is performed by comparing the segmentation result with the manual ground-truth data. The first set of tests was carried out on 27 images that were generated using natural textures from the VisTex database [76] and the performance of the algorithm is assessed using statistical measurements such as the mean error, mode error and median value of the error when several parameters of the algorithm are varied. The performance of the proposed approach is also compared against that attained by the colour–texture segmentation method proposed by Ma and Manjunath [32] and the reported results indicate that Mirmehdi and Petrou's method outperforms the Edge-Flow technique due to its better preservation of the objects' boundaries during the segmentation process. Additional visual results are presented when both algorithms are applied to four natural images. The main limitation of the algorithm developed by Mirmehdi and Petrou [31] is that the colour and texture features are not explicitly used in the proposed segmentation strategy and this may cause problems if one would like to optimise their contribution in the segmentation process. A related coarse-to-fine segmentation approach was proposed by Huang et al. [33]. In this paper the authors applied Scale Space Filters (SSF) to partition the image histogram into regions that are bordered by salient peaks and valleys. This histogram partitioning process represents the

coarse stage of the proposed image segmentation technique while the fine stage implements a Markov Random Field process that is applied to obtain the final result.

Another widely employed segmentation scenario that belongs to this trend starts with the extraction of the dominant colour features, a process which is typically achieved by employing a colour quantisation procedure that is followed by the extraction of the spatial information based on various texture analysis approaches. A well-known technique that follows this sequential colour–texture feature integration approach was proposed by Deng and Manjunath [34] and this algorithm is widely regarded as a benchmark by the computer vision community. The proposed method is referred to as JSEG and consists of two computational stages that are applied in succession, namely colour quantisation and spatial segmentation. During the first stage, the colour information of the input image is sampled by a reduced set of significant colours (between 10 to 20 prototypes) that are obtained after the application of a peer-group filtering colour quantisation technique. This step is performed in the CIE Luv colour space without enforcing the spatial relationship between pixels. The aim of this process is to map the image into a structure where each pixel is assigned a class label. The next stage of the algorithm enforces the spatial composition of the class labels using a segmentation criterion (J value) that samples the local homogeneity. By adopting a coarse-to-fine approach, the segmentation process is defined as a multi-scale region growing strategy that is applied to the J -images, where the initial seeds required by the region growing procedure correspond to minima of local J values. This multi-scale region growing process often generates an over-segmented result, and to address this problem, a post-processing technique is applied to merge the adjacent regions based on colour similarity and the Euclidian distance in the CIE Luv colour space. An important point made by this paper consists in the use of colour and texture information in succession and the authors argue that this approach is beneficial since it is difficult to analyse the colour similarity and spatial relationships between the neighbouring pixels at the same time. In general the overall performance of the JSEG algorithm is very good and to illustrate this fact a number of segmentation results are displayed in Fig. 4. However it is useful to mention that the obtained results depend on the optimal selection of three parameters that have to be *a priori* specified by the user: the colour quantisation threshold, the number of scales and the merge threshold. In the experimental section of their paper, the authors presented the results obtained by the proposed algorithm when applied to several natural images and video data and a large discussion was devoted to analyse the influence of the number of scales on the overall performance of the segmentation process. The authors also reported good results when the JSEG algorithm was applied to 2500 images from Corel photo database without any parameter tuning. Although the concepts behind the implementation of the JSEG algorithm are intuitive, this colour–texture segmentation approach has several limitations. These include the over-segmentation of images characterised by uneven illumination, instability in distinguishing adjacent regions with similar textural patterns and problems in identifying small and narrow details. While the former problem is caused by the rigid quantisation procedure that is applied to extract the colour prototypes in the coarse stage of the algorithm, the latter issues are mainly caused by two factors. The first is generated by the fact that the seed expansion in the region growing process evaluates only the J values (that are able to sample the texture complexity rather than a precise texture model) and in addition the spatial continuity is evaluated in relative large neighbourhoods. The second factor is related to the procedure applied to determine the initial seeds for the region growing algorithm. In the implementation proposed by Deng and Manjunath [34] a size criterion is imposed in the process



Fig. 4. Results obtained using the JSEG segmentation algorithm proposed by Deng and Manjunath [34] when applied to images sampled from the Berkeley database [52]. These results were obtained by setting the JSEG parameters to the following default values: colour quantisation threshold=255, scale=1 and the merge threshold=0.4.

of generating the candidate seed region and this is mainly used to prevent the algorithm to be trapped in local minima. While this requirement is beneficial as it reduces the level of over-segmentation, on the other hand it has a detrimental effect since the small and narrow objects are eliminated from the final segmented result.

To address the abovementioned limitations associated with the original JSEG implementation, different approaches based on the strategy introduced by Deng and Manjunath [34] have been proposed. In this regard, Wang et al. [35] suggested the integration of directional measures into the calculation of the J values and they evaluated the performances of the new JSEG-based algorithm and the original JSEG implementation when applied to 150 images randomly chosen from the Berkeley database [52]. The average percentages of pixels that are differently labelled by the analysed algorithms when compared to the manual segmentations have been reported as 33.1 for JSEG and 24.1 for the algorithm proposed by Wang et al. [35]. In [36,37] the authors replaced the colour quantisation phase of the JSEG algorithm with an adaptive Mean Shift clustering method, while Zheng et al. [38] followed the same idea and combined the quantisation phase of the JSEG algorithm with fuzzy connectedness. Yu et al. [39] attempted to address the over-segmentation problems associated with the standard JSEG algorithm by evaluating an additional measure that samples the colour–texture homogeneity using the photometric invariant edge information. The authors validated the proposed algorithm on 200 images from the Berkeley database [52] and they reported that the Local Consistency Error (LCE) [116] obtained for their method is 24.3% and that attained by JSEG is 36.1%. Following a detailed examination of the JSEG-related implementations, we can conclude that all these algorithmic modifications led to an increase in the number of user-defined parameters that have to be *a priori* optimised and moreover the overall performances of these algorithms were only marginally better when compared to the original implementation proposed by Deng and Manjunath.

Following similar feature integration principles, Krinidis and Pitas [40] introduced an approach called MIS (Modal Image Segmentation) where the multi-scale region growing stage used in the implementation by Deng and Manjunath [34] has been replaced with a deformable model energy function whose external forces combine the intensity of the image pixels with the local spatial image information. Similar to JSEG [34], this algorithm consists of two computational components. The first stage implies a coarse image representation that is obtained by applying a colour quantisation procedure. The main goal of the quantisation stage is to sample the local smoothness in the colour domain, a process that is quantified by a weight value that is assigned to each pixel in the image. During the second stage, the output of the quantisation phase is used to extract the local spatial image information by applying external forces that control the evolution of the Deformable Surface Model (DSM). This process involves calculating an energy functional that measures the smoothness characteristics in the region around each pixel. The final stage of the algorithm implements an agglomerative merging procedure that is applied to alleviate over-segmentation problems. The MIS algorithm was evaluated on all 300 images contained in the Berkeley database [52] using measures such as the Probabilistic Rand (PR) [119], Boundary Displacement Error (BDE) [117], Variation of Information (VI) [118] and Global Consistency Error (GCE) [116]. The MIS colour–texture segmentation technique was compared against four state of the art image segmentation algorithms namely Mean-Shift [41], Normalised Cuts [42], Nearest Neighbour Graphs [43] and Compression based Texture Merging [44] and the reported results are shown in Table 3 (where we provide details in regard to the performance attained by representative state of the art implementations). It is important to note that the performance of the MIS algorithm is highly dependent on the optimal selection of the parameter λ (a coefficient included in the denominator of the Discrete Modal Transform equation) whose influence is analysed in detail by the authors.

The unsupervised segmentation of textured colour images has been recently addressed in the paper by Hedjam and Mignotte [50]. They proposed a hierarchical graph-based Markovian Clustering (HMC) algorithm that consists of two steps. During the first step, the input image is over-segmented into K pre-defined classes using Markov Random Field models while during the second step the resulting image map is modelled as a classical Region Adjacency Graph (RAG) where each edge has associated weights that sample the colour–texture similarity between adjacent regions. Clusters are obtained through edge linking and are represented by dense regions of strongly connected nodes. In the experimental section, the authors have conducted a comprehensive quantitative performance evaluation of the proposed technique when applied to the entire Berkeley Database [52] by calculating performance metrics such as Probabilistic Rand Index (PR) [119], Variation of Information (VI) [118], Global Consistency Error (GCE) [116] and Border Displacement Error (BDE) [117]. A related algorithm that also approached the integration of the colour and texture features as a serial process has been described in [51]. This segmentation technique consists of three computational steps. In the first step the input image is partitioned using a tree structured Markov Random Field (TS-MRF) algorithm which implements a recursive splitting procedure until the colour range of the resulting regions is consistent with some uniformity criteria. The second step of the algorithm evaluates the spatial information within the regions obtained from the first step, while the last step applies a region-merging process to identify the image areas with homogenous texture characteristics. The proposed algorithm has been tested on mosaic images from the Prague Texture Segmentation Data-Generator and Benchmark [134] (see Table 2) and the experimental results indicate that this segmentation scheme shows limitations in identifying the transitions between textures that are characterised by irregularities in the spatial or colour domain.

A different feature integration approach was adopted by Gevers [45] where a split and merge image segmentation technique was developed for the retrieval of complex images that are subjected to changes in viewpoint and illumination conditions. To this end, the author extracted the histograms of the colour ratio gradients from the original RGB image and the process applied to partition the image into colour–texture homogenous regions is based on a split and merge strategy. While the image resulting after the application of the split and merge processes is often over-segmented, to eliminate the small spurious regions a post-processing step based on region growing is applied.

As opposed to previous approaches, in the early work by Jain and Chen [46] the texture attributes were more elaborately analysed when compared to the colour information. In this paper the authors combined the colour and texture features in the development of a multi-phase segmentation algorithm that has been specifically designed to perform the automatic identification of address blocks in colour magazines. The first stage of their algorithm entails a colour thresholding technique to obtain a binary image that is used in the process of extracting the texture information using a multi-channel Gabor filtering strategy that was earlier proposed in the paper by Jain and Farrokhnia [47]. This segmentation scheme involves a statistical data partitioning process where each pixel in the image is mapped to a representation defined by the Gabor features that are augmented with the pixel coordinates. Due to its simplicity, this approach proved to be popular among vision researchers, as it offers an intuitive framework to attain the integration of the colour and texture attributes into the segmentation process. Since the texture analysis has played a critical role in the development of various segmentation schemes, we would like to draw attention to the paper by Randen and Hussoy [48] where a large number of filtering-based texture

analysis schemes were contrasted and evaluated. This initial study has been further advanced in the paper by Reyes-Aldasoro and Bhalerao [49] where the authors focused on several issues relating to feature selection, optimal distance metric and multi-resolution classification. Based on the experimental results reported for several well-known texture analysis techniques, the authors conclude that the use of feature selection in conjunction with multi-resolution classification can improve considerably the classification results attained by the standard texture analysis techniques.

2.3. Approaches that extract colour and texture features on independent channels

As opposed to the segmentation techniques reviewed in the previous section where the integration of the colour and texture attributes is performed in a sequential manner, the methods that comprise this category extract the colour and texture features on independent channels. Approaches that belong to this trend are developed based on the assumption that colour and texture are differently modelled when analysed from a statistical point of view and one obvious advantage associated with these methods (when compared to the techniques discussed in the previous subsection) is that their contributions can be optimised when they are integrated in the segmentation process. Based on the concepts behind this integration strategy, the methods belonging to this category can be subdivided into two distinct groups. The first sub-category combines the extracted colour and texture features using region-based feature integration schemes such as split and merge, region growing and active contours. The region-based approaches are arguably the most investigated segmentation schemes in the field of colour–texture analysis and this is motivated by the fact that the spatial coherence between adjacent pixels (or image regions) is enforced during the segmentation process. The second sub-category is defined by the feature integration schemes based on statistical and probabilistic strategies. In this latter category, boundary detection algorithms and learning-based methods have also been investigated in the context of colour–texture segmentation. In the next subsections of the paper we will review several representative approaches that are included in each sub-category that was introduced above.

2.3.1. Colour–texture segmentation using region-based integration

2.3.1.1. Colour and texture integration using split and merge techniques. The split and merge methods start in general with an inhomogeneous partition of the image and they agglomerate the initial partitions into disjoint regions with uniform characteristics. There are two distinct stages that characterise these techniques. In the first phase (splitting) the image is hierarchically divided into sub-blocks until a homogeneity criterion is upheld, while in the second stage (merging) the adjacent regions that have similar properties are joined, usually using a Region Adjacency Graph (RAG) data structure. An important limitation of the split and merge techniques resides in the fact that the initial partition resulting from the split stage is formed by rectangular regions. Thus, the result obtained after the application of the merge stage has a blocky structure that is not able to accurately capture the shape of the imaged objects. To compensate for this problem, the image resulting from the merge stage is further post-processed by applying refinement techniques where the pixels situated on the borders are re-classified using some similarity criteria. Also, it is useful to mention that the minimum size of the region resulting from the split process is an important parameter that influences the overall performance of the segmentation algorithm. In this regard, if the region size is too small,

the features calculated in the region under analysis will have low statistical relevance and this has a negative influence towards the decisions that will be made in the merge stage. On the other hand, if the region size is set to large values, the statistical relevance of the features in the region is increased but this is achieved at the expense of missing small and narrow objects in the input image.

Using the concepts discussed above, Ojala and Pietikainen [53,54] proposed a split and merge segmentation algorithm where the texture is locally sampled by the joint distribution of the Local Binary Pattern (LBP) and Contrast (C) features. This approach has been applied to the segmentation of greyscale images and we discuss it in this review as it has attracted substantial interest from the computer vision researchers. Thus, building on Ojala and Pietikainen's work, in [55] the colour features are extracted from the smoothed input image using a self-initialised Expectation-Maximisation (EM) algorithm and the texture features are sampled from the luminance component using the local LBP/C distributions. The segmentation process is implemented using a split and merge strategy where the split and merge phases are controlled by user-defined parameters. Similar to the algorithm proposed in [53], during the merge stage, the similarity between all pairs of adjacent regions resulting from the split process is evaluated using a metric called Merging Importance (MI) and the adjacent regions with the smallest MI are merged. Since the MI values sample the colour–texture characteristics within the image, the authors devised a scheme that is able to locally adapt to the image content by evaluating the uniformity of the colour distribution. Thus, if the colour distribution is homogenous (it is defined by one dominant colour), the weights w_1 and w_2 , that control the contribution of the texture and colour during the merge process are adjusted in order to give the colour information more importance. Conversely, if the colour distribution is heterogeneous it is assumed that the texture is the dominant feature in the image and the algorithm allocates more weight to texture in the calculation of the MI values. The merge process is iteratively applied until the minimum value for MI is

higher than a pre-defined threshold. A typical splitting phase is graphically displayed in Fig. 5(a), while the merging phase is illustrated in Fig. 5(b). To compensate for the blocky structure of the image resulting after the merge step, the authors applied a post-processing step that implements a pixelwise classification procedure. Fig. 6(e) displays the blocky segmentation resulting after the merging step, while 6(f) presents the final segmentation result obtained after pixelwise classification. Chen and Chen [56] adopted a similar split and merge approach for colour–texture segmentation. In this paper, the authors introduced an algorithm that combines the colour and the Local Edge Patterns (LEP) using feature distributions. In the first stage of the algorithm a colour quantisation based on a cellular decomposition strategy was applied in the HSV (Hue Saturation Value) colour space to extract the dominant colours in the image. The next step involves the extraction of two independent feature distributions from the quantised colour image, namely the colour and local edge pattern histograms. These distributions are used to partition the image using a split and merge strategy where the weights that enforce the contribution of colour and texture in the image partitioning process were set to 0.6 for colour and 0.4 for texture. Nammalwar et al. [57,58] presents a similar strategy where the colour and texture are collectively integrated in a split and merge segmentation scheme. In their paper, the texture features are calculated using the Local Binary Pattern technique, while the colour features are extracted using the standard K-means clustering procedure. The proposed method was tested on mosaic and natural images and the experimental results demonstrate that the inclusion of the colour distribution in the merge process proved to be the key issue in achieving accurate segmentation.

2.3.1.2. Colour and texture integration using region growing. The main drawback associated with the split and merge strategies resides in the poor correlation between the regions resulting from the merge step and the borders between contextually coherent

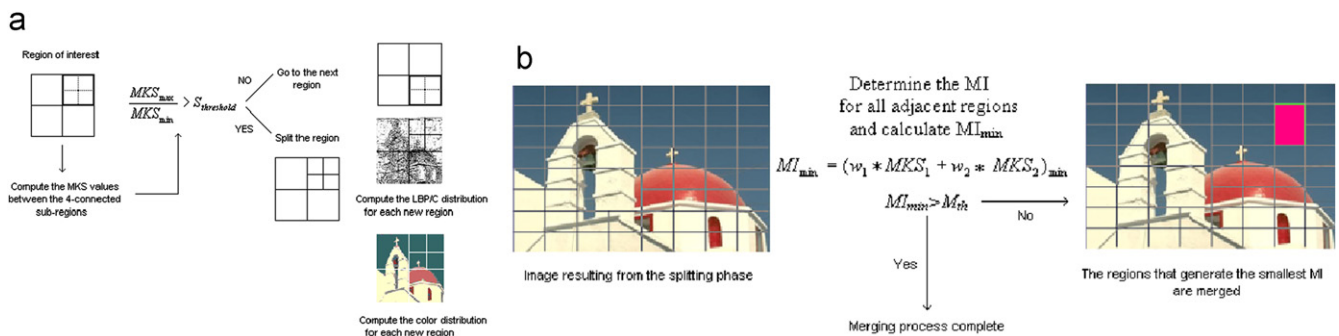


Fig. 5. (a) The split stage of the algorithm proposed in [55]. The hierarchical splitting recursively splits the input image into four sub-blocks if the ratio of the minimum and maximum similarity (calculated using Modified Kolmogorov–Smirnov statistics (MKS) for the six pairwise values between the LBP/C distributions of the four sub-blocks) is higher than a given threshold. (b) The merge phase of the image segmentation algorithm. The adjacent regions with the smallest MI are merged. This is highlighted in the right hand side image. The image used in these diagrams belongs to Berkeley database [52].

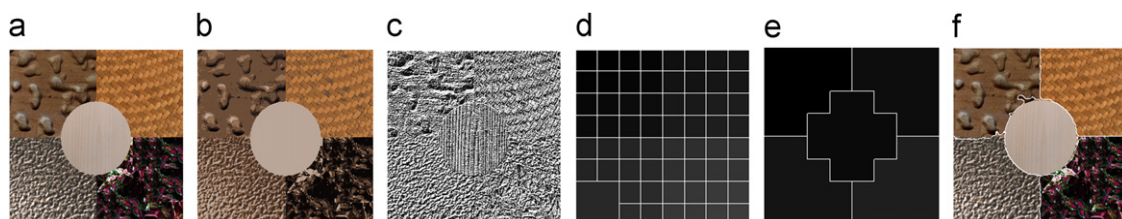


Fig. 6. The segmentation process using the algorithm proposed in [55]: (a) original mosaic image [76], (b) the image resulting from the EM colour segmentation, (c) the texture image information, (d) the image resulting from the split stage, (e) the image resulting from the merge stage and (f) The final segmentation result after pixelwise classification.

objects in the image. To circumvent the issues related to the poor border localisation, region growing techniques have been investigated as an alternative option to split and merge strategies. In general, the region growing methods start with a selection of initial seeds that are iteratively expanded based on some homogeneity criteria. The main advantage of these techniques resides in the fact that the contextual information is preserved during the iterative seed growing process, but their performance is highly dependent on the appropriate selection of the initial seeds. After reviewing a number of relevant region growing colour–texture segmentation techniques we conclude that these approaches place a high level of confidence on the seed initialisation process and on the optimal selection of a set of threshold parameters that are employed to evaluate the local homogeneity in the colour–texture domain. As a result, these segmentation techniques have difficulty in adapting to problems caused by image noise, shadows and uneven illumination.

Garcia Ugarriza et al. [59] proposed an automatic Gradient SEGmentation algorithm (referred to as GSEG) for the segmentation of natural images, that combines the colour and texture features using region growing and a multi-resolution merging. In the first stage of the algorithm, smooth colour regions are identified using colour edge-detection and histogram analysis in the CIE Lab colour space. This information provides an initial segmentation map, where smooth regions are involved in the seed formation process. These seeds are further employed to initialise a region growing procedure that is applied to achieve an initial region growth map. On a different computational strand, the texture information is extracted from the quantised CIE Lab input

data. In the implementation detailed in this paper, the texture information is sampled by the local entropy information associated with each seed. In the last step of the algorithm the texture features, colour and the region growth map are integrated in a region-merging procedure where the similarity of colour and texture features is quantified by the Mahalanobis distance. The main steps of this algorithm are displayed in Fig. 7, when the GSEG algorithm is applied for the segmentation of a natural image [52].

The authors evaluated the proposed segmentation method on the entire Berkeley database [52] using the Normalised Probabilistic Rand (NPR) Index [61] and compared the obtained results against two state of the art segmentation algorithms: JSEG proposed by Deng and Manjunath [34] and the Gibbs Random Field based method (GRF) proposed by Saber et al. [60]. The reported results are as follows: $\text{NPR_GSEG}=0.8$, $\text{NPR_JSEG}=0.7$ and $\text{NPR_GRF}=0.55$ (see Table 3). In Fig. 8 is illustrated a comparison of segmentation results obtained when GSEG, the algorithm proposed in [63] and JSEG are individually applied to a natural image from Berkeley database.

A similar strategy to integrate the colour and texture information has been adopted by Chen et al. [63] in the implementation of an algorithm for the segmentation of natural images into perceptually distinct regions with application to content-based image retrieval (CBIR). In their approach, the local colour features are extracted using a spatially Adaptive Clustering Algorithm (ACA) [62], while the texture features are computed on a different channel using a multi-scale frequency decomposition procedure. The colour and texture features are integrated using a region growing algorithm that generates a primary segmentation that is further

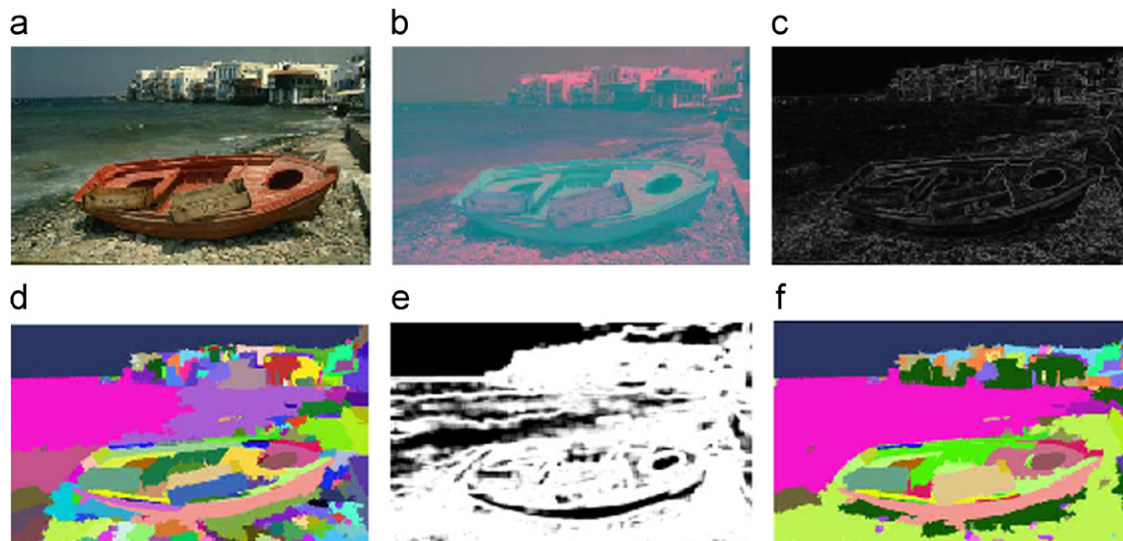


Fig. 7. Intermediate steps of the GSEG algorithm proposed by Garcia Ugarriza et al. [59]: (a) original image from Berkeley database, (b) the CIE Lab colour converted image, (c) gradient map. (d) Seed map obtained after region growth, (e) texture channel and (f) final segmentation map. Images courtesy of IEEE (©[2009] IEEE).

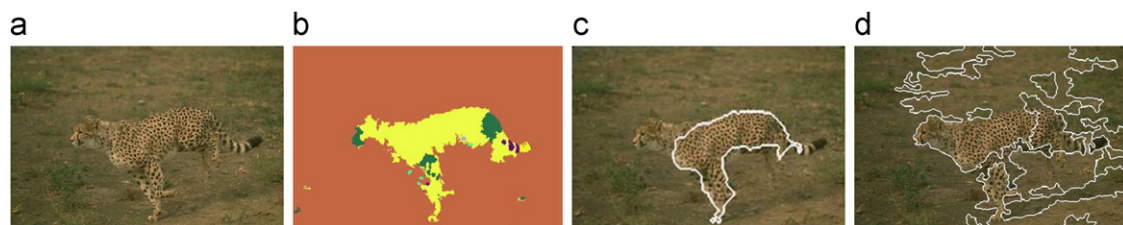


Fig. 8. (a) Original natural image [52], (b) GSEG segmentation map [59], (c) segmentation result based on steerable filter decomposition proposed by Chen et al. [63] and (d) segmentation result obtained using the JSEG algorithm [34] (colour quantisation threshold=255, scale=1 and merge threshold=0.4). Images (b) and (c) courtesy of IEEE (©[2009], [2005] IEEE).

improved by the application of a post-processing step that implements a border refinement procedure. Although limited, the experimental data reported in this paper indicate that this approach returns accurate results, but its main disadvantage resides in its substantial level of supervision since the number of classes required by the clustering algorithm is a user-defined parameter. In [64], Paschos and Valavanis proposed an improved version of their early approach in [25] and chose to separately extract the colour and texture features from the image converted to xyY colour space and then combine them using a region growing procedure. Texture information is extracted from the luminance channel Y using a set of filters tuned to different sizes and orientations that will be further smoothed and processed in order to obtain a boundary image. Colour is separately extracted from the chrominance channels (xy) and homogenous regions are identified using a threshold-driven process that partitions the chrominance histogram. For image segmentation, the extracted boundary and colour-based information are further combined using a region growing algorithm. The authors tested the proposed segmentation methods on aerial images of wetland scenes. Other approaches that belong to this category include the works of Fondon et al. [65] where colour is analysed in the CIE Lab space and combined with the texture features using multi-step region growing and Grinias et al. [66] that proposed a segmentation framework using K -Means clustering followed by region growing in the spatial domain.

2.3.1.3. Colour and texture integration based on energy minimisation. Another strategy adopted by researchers to integrate the colour and texture information is to approach the segmentation problem in terms of energy minimisation. Active contours are a distinct category of region-based segmentation techniques that aim to iteratively deform an initial contour by minimising energies that relate to the intrinsic properties of the contour and those dependent on the image data. The techniques that are included in this category achieve accurate performance, but their main drawback consists in the high level of supervision required to select the initial contour. In addition, active contours approaches consist of iterative procedures that are computationally intensive and in general they are better suited for applications where strong knowledge in regard to the shape of the objects of interest is available. Graph-based minimisation techniques are also included in this category and their major aim is focused on integrating the colour and texture features with the purpose of finding the minimum cut in a weighted graph.

Freixenet et al. [67] proposed to combine the region and boundary information for colour–texture segmentation. To achieve this goal, they employed an energy minimisation approach where the initial seeds are sampled from the regions obtained as a combination of perceptual colour and texture edges. To this end, the combined colour–texture properties of the image regions were modelled by the union of non-parametric kernel density estimators and classical co-occurrence matrices, where initial seeds compete for feature points by minimising an energy function based on hybrid active regions that takes both region and boundary

information into account. The boundary term of the energy function is given by the probability that the boundary pixels are edge pixels, while the region term measures the homogeneity inside the region. In Fig. 9 are displayed segmentation results of six mosaic images, as presented by the authors in their paper.

A related approach has been recently proposed by Sail-Allili and Ziou [68] where the colour–texture information is sampled by compound Gaussian Mixture Models. Similar to the algorithm proposed by Freixenet et al. [67], the colour–texture integration task is defined in terms of minimising an energy function. Another related technique was developed by Luis-Garcia et al. [69], where the local structure tensors and the image colour components were combined within an energy minimisation framework to accomplish colour–texture segmentation. In their paper, the parameter that controls the influence of the image data in the energy minimisation process was calculated as $\beta_1/(\beta_1 + \beta_2)$, where β_1 and β_2 weight the contribution of the structure tensor and image components, respectively. The authors propose an algorithmic solution to adaptively select these two parameters. Thus, the parameter β_1 is selected based on a measure of overlap (Q) between the two texture distributions that correspond to the foreground and the background respectively. If the analysed texture distributions are substantially dissimilar, then Q takes a small value and the algorithm assigns a high weight ($\beta_1 = (1 - Q)$) to the texture information. The colour weight β_2 is given by the Euclidian distance between the mean values of the two regions. The authors demonstrate through experimentation that substantially better results are achieved when the weights that control the contribution of the colour and texture in the energy minimisation process are dynamically determined when compared to the situation when the colour and texture are given equal weights, i.e. $\beta_1 = \beta_2$.

A graph-based implementation has been recently proposed by Han et al. [73], where they introduced a new segmentation framework that was developed to identify the foreground object in natural colour images. The colour features are extracted from the CIE Lab converted colour image, while the texture features are computed from the luminance component of the input image using the multi-scale non-linear structure tensor (MSNST). The MSNST is based on the generalisation of the classic structure tensor and this feature extraction strategy resembles many similarities to the Gabor wavelets by allowing the analysis of the image orientation at different scales. To reduce the dimensionality of the colour–texture feature space, the colour information is clustered using a binary tree quantisation procedure while the features in the texture domain are clustered using a K -means algorithm. The resulting colour and texture features are modelled by Gaussian Mixture Models (GMMs) and integrated into a framework based on the GrabCut algorithm [74]. To further improve the accuracy of the algorithm, the authors proposed an adaptive feature integration strategy that consists in adjusting a weighting factor for colour and texture in the segmentation process. This was implemented by using an approximation of

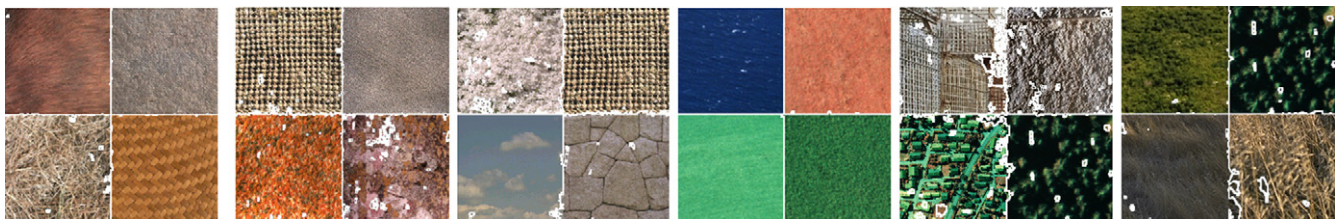


Fig. 9. Colour–texture segmentation results obtained when the algorithm developed by Freixenet et al. [67] was applied to six mosaic images. The borders between objects are marked in white. Images courtesy of Freixenet et al. [67].

the Kullback–Leibler (KL) divergence to evaluate two probability density functions that model the characteristics of the foreground and background information in the image data. The authors evaluated the performance attained by the algorithm discussed in their paper on synthetic and natural images and they performed side-by-side comparisons with the results returned by the standard GrabCut algorithm [74]. An example when the segmentation result obtained using the proposed MSNST algorithm is compared against that obtained using the standard GrabCut is illustrated in Fig. 10. One disadvantage associated with the proposed algorithm is the substantial level of user interaction that is required to place the initial contour around the object of interest (see Fig. 10(a)). Also the algorithm is designed to segment only the selected foreground object and its performance is influenced by the optimisation of a large number of parameters.

Kim and Hong [75] also defined the colour–texture segmentation as the problem of finding the minimum cut in a weighted graph. In their approach the colour information is represented by the RGB feature vector, while texture features are characterised by the textons that are determined by filtering the image with a Gabor filter bank. In order to enforce a spatially coherent representation, the extracted texture vectors are clustered using a *K*-means algorithm, where the number of clusters is set to 12. The original RGB image components and the normalised texton feature vectors are concatenated in a multi-dimensional vector and the unsupervised segmentation is formulated in terms of energy minimisation of a weighted graph, where the minimum cuts are found by applying a splitting approach. The performance of the proposed algorithm called UGC (Unsupervised Graph Cuts) is compared against JSEG [34] using standard metrics such as precision and recall. The experiments were conducted using images selected from the VisTex [76] and Berkeley databases [52] (refer to Table 3 for detailed results).

Level sets approaches have also been evaluated in the context of colour–texture analysis and we would like to draw attention to the review presented by Cremers et al. [70]. The authors focused on a thorough theoretical description of region-based level-set segmentation methods where the image domain is partitioned by integrating various features (colour, texture and shape) into a set of cost functionals. The main conclusion that can be drawn from their paper is that the methods that implement the segmentation as an energy minimisation process have the advantage of enforcing strong geometrical constraints during boundary propagation, but it is useful to note that this advantage is achieved at the expense of increasing the level of supervision, as several parameters need to be specified *a priori* to control the evolution of the algorithm at each iteration. Recent studies that present improvements of the active contours in capturing complex geometries and dealing with difficult initialisations can be found in [71,72].

Brox et al. [77] propose to combine colour, texture and motion in a level-set image segmentation framework. They first create a

joint feature vector composed of the three colour channels of the CIE Lab colour space, three texture features given by the components of the spatial structure tensor and two motion components that are extracted using an optical flow algorithm. In the next step, a coupled non-linear diffusion process is applied to improve the spatial coherence between the feature channels and enhance the edges between perceptually uniform regions in the image. Finally, the smoothed features are modelled by a joint probability density function and the final image segmentation is obtained by maximising the a posteriori probability using a level-set technique.

Colour and texture integration using active contours and energy minimisation approaches have been intensively investigated in recent years, mainly because they represent active image models that tend to position themselves very close to the desired object contours by minimising an energy functional. However, the performance of the energy minimisation-based segmentation schemes is strongly dependent on the user interaction – the more prior image information, the better the performance of the algorithm. Therefore, in spite of the usefulness and good performance of these methods, the high level of supervision can be seen as a drawback considering that the colour–texture segmentation field is heading towards completely automatic approaches. To answer this requirement, the feature-based approaches have positioned as an attractive and viable alternative to energy minimisation segmentation algorithms and these methods will be analysed in the following subsection.

2.3.2. Colour–texture segmentation using feature-based integration

The feature-based colour–texture segmentation algorithms were developed building on the assumption that the separately extracted colour and texture features are locally homogeneous and the segmentation task can be viewed as a statistical or probabilistic image partitioning process. Consequently, these colour–texture approaches can be broadly sub-categorised based on the nature of the algorithm employed for feature integration. In this regard, statistical data partitioning techniques include: generalised *K*-means, fuzzy clustering, neural networks, multi-dimensional clustering and learning-based approaches. The probabilistic colour–texture integration schemes are based on Bayesian classification, Expectation-Maximisation and Markov Random Fields.

2.3.2.1. Colour–texture integration using statistical approaches.

Zoller et al. [78] formulated the image segmentation as a data clustering process where the colour and texture features were combined using a parametric distributional clustering (PDC) approach. In this implementation the colour features were given by the three components of the HSV colour space, while the texture features were extracted by convolving the *V* component of the image with a set of Gabor filters with four orientations. The authors applied the proposed algorithm to the segmentation of a small set of

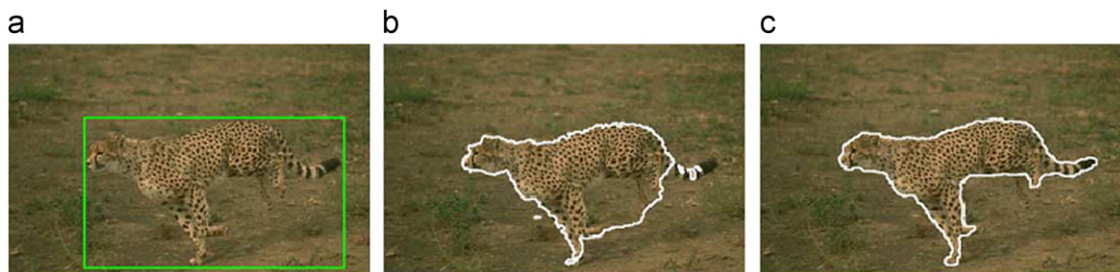


Fig. 10. (a) The initial contour is placed around the object of interest in a natural image from Berkeley database [52], (b) the segmentation result obtained using the standard GrabCut method [74] and (c) the result obtained using the MSNST segmentation algorithm proposed by Han et al. [73]. Images courtesy of IEEE (©[2009] IEEE).

natural images and the results were compared against those returned by the Normalised Cuts method [42]. The most interesting aspect associated with this work is the parameter optimisation procedure applied for model identification that was embedded in a deterministic annealing framework. A related segmentation approach to integrate the colour and texture features was proposed by Ooi and Lim [79]. In their paper, the authors were in particular concerned with issues related to the optimal selection of the colour space and the extraction of the most representative texture descriptors. Thus, eight colour spaces (RGB, XYZ, YIQ, YCbCr, $I_1I_2I_3$, HSV, HIS and CIE Lab) were empirically evaluated in their study and the conclusion resulting from this investigation is that the best segmentation results are obtained when the input image is converted to the CIE Lab colour representation. The texture features were extracted from the L component using the contrast and entropy of the co-occurrence matrices that are calculated for each pixel in the image. The fusion of colour (ab components) and texture features (contrast-entropy features of the Grey Level Co-occurrence Matrix—GLCM) is implemented using a fuzzy c -means clustering strategy. The proposed algorithm was applied to content-based image retrieval (using a database consisting of 4000 images) and the performance of the retrieval process was assessed using the precision and recall metrics. One limitation of this approach resides in the fact that the colour and texture information are integrated at pixel level and this issue generates errors when dealing with local distortions in the local colour–texture content.

Although clustering methods [83] have been widely applied in the development of colour–texture segmentation algorithms due to their simplicity and low computational cost, it is useful to note that the performance of these approaches is critically influenced by two essential conditions: (a) the improper initialisation of the cluster centres that will force the algorithm to converge to local minima and produce erroneous results and (b) the difficulty in selecting the optimal number of clusters (generally, this parameter is user defined). Consequently, the colour–texture information is not optimally evaluated during the space partitioning process if the clustering algorithms are initialised on outliers or the number of clusters is incorrectly chosen. As a result, substantial research efforts have been devoted to develop robust initialisation schemes and to evaluate

diverse algorithmic solutions to identify the optimal number of clusters in the input image. These issues have been specifically addressed in a recent colour–texture segmentation framework (referred to as CTex) [80,81], where colour and texture are investigated on separate channels. In this approach, the colour segmentation is the first major component of the proposed framework and involves the statistical analysis of data using multi-space colour representations. The first step of the colour segmentation involves filtering the input data using a Gradient-Boosted Forward and Backward (GB-FAB) anisotropic diffusion algorithm [82] that is applied to eliminate the influence of the image noise and improve the local colour coherence. The authors have identified the selection of the number of clusters and the initial cluster centres as the most difficult problems that have to be addressed in the implementation of statistical data partitioning schemes. To tackle this problem, the first stream of the colour segmentation algorithm extracts the dominant colours and identifies the optimal number of clusters from the first colour representation of the image using an unsupervised procedure based on a Self Organising Map (SOM) network. The second stream of the proposed colour segmentation scheme analyses the image in a complementary colour space where the number of clusters calculated from the first colour representation performs the synchronisation between the two computational streams of the algorithm. In the final stage of the colour segmentation process, the clustered results obtained for each colour space form the input for a multi-space clustering process that outputs the final colour segmented image. The second major component of the proposed CTex framework involves the extraction of the texture features from the luminance component of the original image using a multi-channel texture decomposition technique based on Gabor filters. The colour and texture features are integrated in an Adaptive Spatial K -Means (ASKM) framework that partitions the data mapped into the colour–texture space by adaptively sampling the local texture continuity and the local colour smoothness in the image. Segmentation results obtained using the CTex framework are illustrated in Fig. 11.

Campbell and Thomas [85] proposed a conceptually related algorithm where the extracted colour and texture features are concatenated into a feature vector and then clustered using a randomly initialised Self Organising Map (SOM) network. In their



Fig. 11. Results obtained using the CTex colour–texture segmentation algorithm proposed in [80], when applied to images sampled from the Berkeley database [52]. For visualisation purposes, the objects borders are superimposed on the original image.

implementation the colour features are extracted using three low-pass colour filters, while texture features are determined using 16 Gabor filters. The proposed segmentation technique was tested on natural images taken from the Bristol Image Database [137] and the segmentation results were compared against manually annotated ground-truth data. The reported average segmentation accuracy is as follows: 36.4% when using only texture features, 55.7% when using only colour features and 62.2% when using combined colour–texture features. Other related approaches that integrate colour and texture features using clustering methods can be found in [86–92].

Liapis and Tziritis [93] proposed an algorithm for image retrieval where the colour and texture are independently extracted and the dissimilarity between images is evaluated using the Bhattacharya distance. In their implementation, the texture features were extracted using a Discrete Wavelet Frame analysis and modelled using Laplacian distributions, while the colour features were defined by the quantised 2D histograms of the chromaticity components of the image converted to the CIE Lab colour representation. For the validation of the proposed retrieval system and comparison with other methods and implementations, Liapis and Tziritis' first set of tests were conducted using texture information alone on Brodatz images [94], a database composed of 112 grayscale textures. This database was used in the evaluation so that the authors could benchmark their retrieval method against other similar works published in literature based on texture analysis. In addition, the authors also recorded retrieval results using colour-alone, texture-alone and combined colour–texture features when using 55 colour natural images from VisTex [76] and 210 colour images from Corel Photo Gallery. The purpose of these tests was to demonstrate that higher retrieval performance is obtained when colour and texture features are combined, as a drop in performance is recorded when using texture-alone or colour-alone information. In the experimental section the authors concluded that the developed technique was able to return good performance for “quasiperiodic texture patterns” while poorer results for random or chaotic patterns”.

Martin et al. [95] adopted a different approach for the boundary identification of objects present in natural images. The authors proposed a supervised learning procedure to combine colour, texture and brightness features by training a classifier using the manually generated ground-truth data taken from the Berkeley segmentation dataset [52]. In the first stage of the algorithm, four local features are independently extracted for each pixel in the image: the colour gradient, the texture gradient, the oriented energy and the brightness gradient. These features were employed to

measure the local variation in the luminance (L) and chrominance (ab) channels of the input image and each feature has been individually optimised with respect to the ground-truth data where the objective is to search for high precision and recall values. In this process 200 images were used to train the classifier, while 100 images were used for testing. The output of the classifier provides the boundary posterior probability at each image location and orientation. In order to evaluate their algorithm, the authors demonstrated that the proposed technique outperforms two classical boundary detection algorithms (Canny edge detector [96] and the spatially averaged second moment matrix) with respect to the F -measure values [123]. In line with the substantial level of supervision, Hanbury and Marcotegui [97] identified another problem associated with the approach proposed by Martin et al. [95], namely the existence of gaps in the identified boundary lines. To address this issue, they applied a distance transform to the greyscale probability image and the resulting boundaries determined in the colour–texture feature space were fused with those returned by a hierarchical watershed procedure in order to obtain the final segmentation result. The authors compared the performance of the proposed method against that attained by the Normalised Cuts segmentation algorithm [42] and the numerical evaluation was carried out by computing the mean GCE [116], precision, recall and F -measure values for all images in the Berkeley database [52]. The results reported by the authors are included in Table 3.

2.3.2.2. Colour and texture integration using probabilistic approaches. Carson et al. [98] proposed a colour–texture segmentation scheme (that is referred to as Blobworld) that was designed to achieve the partition of the input image in perceptual coherent regions. The central novelty associated with this work resides in the inclusion of the anisotropy, polarity and contrast features in a multi-scale texture model. The colour features are extracted on an independent channel from the CIE Lab converted image that has been filtered with a Gaussian operator. For automatic colour–texture image segmentation, the authors proposed to jointly model the distribution of the colour, texture and position features using Gaussian Mixture Models (GMMs). The main advantage of the Blobworld algorithm consists in its ability to segment the image into compact regions and the authors evaluated its suitability in the development of a content-based image retrieval system. Illustrative segmentation results obtained using the Blobworld scheme are displayed in Fig. 12.

Another probabilistic scheme to integrate the colour and texture information in the segmentation process has been



Fig. 12. Segmentation results (second row) obtained when the Blobworld technique proposed by Carson et al. [98] is applied to three images from Corel Photo gallery (first row).

proposed by Manduchi [99]. In this approach the author has extracted the colour and texture features on independent channels, where the mixture models for each class were estimated using an Expectation-Maximisation (EM) algorithm. The most interesting aspect associated with this work is related to the feature fusion process where a “Cartesian product” operator was employed to merge the colour and texture models. One disadvantage associated with this approach is the large number of classes generated by the colour–texture integration process and to alleviate the over-segmentation issues the author applied a class reduction technique based on a maximum descriptiveness criterion. Jolly and Gupta [100] followed a similar approach where the colour and texture features were extracted on separate channels. In their algorithm the texture features are determined using multi-resolution autoregressive models and the colour features are defined by the chrominance components in two colour spaces. In each separate feature space, the maximum likelihood is calculated and the final segmentation is obtained by combining the two likelihoods using some pre-defined fusion criteria. The proposed method was applied to the segmentation of mosaic and aerial images and the experimental results demonstrate that the use of combined colour–texture features significantly improves the segmentation results. Based on the conclusions that arose from the interpretation of the experimental results, the authors argued that the independent extraction of the colour and texture features is opportune since this approach allows the development of flexible feature integration strategies. A similar combinational approach was adopted by Khan et al. [101]. In their implementation, the input image is converted to the CIE Lab colour space prior to the calculation of the colour and texture features. The texture features are extracted from the *L* image component using a standard image decomposition scheme based on Gabor filtering. The colour features are given by the chromatic *ab* image components. The colour–texture feature vector is constructed by concatenating the following components: intensity gradient and local energy content of the *L* channel, three colour features (colour gradient and the local energy content of the *a* and *b* components), three texture features (intensity, phase divergence and homogeneity), and the position (*x*, *y*) features of the pixel coordinates. The distribution of these features is modelled using a mixture of Gaussians whose parameters are estimated using an EM algorithm. In order to initialise the number of mixture models, the authors used histogram analysis and employed the Schwarz criterion to determine the optimal number of clusters. The quantitative evaluation of the proposed algorithm was carried out on a restricted set of images from the Berkeley database by using the hit rate metric, which was defined as the percentage of pixels that have been assigned the same cluster label in the segmented and ground-truth data. The reported hit rate values for all images evaluated in their study were in the range [97%, 99.5%]. Because only a small number of images were used in their experimental activity, it is difficult to fully evaluate the performance of this technique when compared to other implementations. A related approach was adopted by Fukuda et al. [102] with the purpose of segmenting an object of interest from the background information. The RGB colour features are combined into a multi-dimensional feature vector with the local texture features given by the wavelet coefficients. The colour–texture integration is modelled using Gaussian Mixture Models (GMMs) and the segmentation process is carried out in a coarse-to-fine fashion using an iterative process to find a minimum cost in a graph.

Approaches based on Markov Random Field (MRF) models were often employed for texture analysis [103–105]. The main motivation behind their popularity among vision researchers is given by the fact that the MRF models are able to capture the spatial dependence between pixels, since the probability of a pixel

taking a certain intensity value depends only on the intensity values of the pixels situated in its neighbourhood. Using this approach, Kato and Pong [105] adopted a MRF model-based colour–texture segmentation strategy that is formulated as a global optimisation technique using simulated annealing. In their implementation the colour features are given by the CIE Luv colour components, while the texture features are extracted using a bank of even-symmetric Gabor filters. Similar to the approach proposed by Khan et al. [101], the extracted features are modelled using Gaussian distributions, where the mixture parameters are estimated using an Expectation-Maximisation (EM) algorithm. Another method that fits in this category was proposed in [106] where an auto-binomial Gibbs Markov Random Field was used for texture modelling, whereas a 2D Gaussian distribution was used to sample the colour information. The colour and texture features were fused by estimating their joint probability distribution function at region level. Other approaches that employed MRF models for colour–texture segmentation include the works detailed in [107–113]. Although the MRF-based colour–texture segmentation attracted some interest from vision researchers, the main drawback of these methods consists in their inability to adapt to local distortions in textures that are commonly encountered in natural images and their onerous computational overhead.

3. Evaluation methodologies (measures, databases, benchmarks and performance evaluation)

3.1. Evaluation measures

An essential aspect in the development of colour–texture segmentation algorithms is the quantitative evaluation of the obtained results. Since the segmentation of natural images involves a substantial level of subjectivity, the process required to evaluate the segmentation accuracy is far from a trivial task. A survey of segmentation evaluation methods that do not require manually annotated ground-truth data is provided in [114,115]. These techniques analyse the segmented result using metrics that measure the intra-region uniformity and inter-region disparity and in general they provide only global indicators that assess the quality of the segmentation process. However, due to the complexity and subjective interpretation of the images obtained by the colour–texture segmentation algorithms, the evaluation methods that statistically compare the segmentation results against ground-truth data gained the largest acceptance from the computer vision community. In the remainder of this section we will focus on summarising and discussing the most relevant performance evaluation metrics that are most commonly applied to quantify the accuracy of colour–texture segmentation techniques with respect to the ground-truth data. The performance evaluation metrics evaluated in this study are listed in Table 1.

The accuracy of the segmentation process can be quantified by measuring the degree of overlap between the clusters in the segmented result and the ground-truth data. In this regard, the Local Consistency Error (LCE) and the Global Consistency Error (GCE) [116] are examples of area-based metrics that sample the level of similarity between the segmented and ground-truth data by summing the local inconsistencies for each pixel in the image. The major drawback associated with the LCE and GCE is that they return a meaningful evaluation result only when comparing two images that have the same number of labels, a situation that rarely occurs in practice, unless the number of clusters is a user-defined parameter. Hence, in the case of unsupervised segmentation, the number of clusters is not known *a priori*, and as a result the LCE and GCE cannot be directly applied to quantify the segmented results.

Table 1

Summary of representative segmentation evaluation measures proposed in literature (GT=ground-truth data and S=segmented image).

Segmentation evaluation measure (and corresponding reference paper)	Summary
Local Refinement Error (LRE) [116]	LRE is calculated for each pixel x_i in the image as the normalised difference between the cardinality of the region that belongs to the pixel x_i in the segmented image and the cardinality of the region that belongs to the pixel x_i in the GT image
Global Consistency Error (GCE) and Local Consistency Error (LCE) [116]	These measures extend the LRE from pixel level to image level by summing up all local inconsistencies for each pixel in the image. These are region-based measures of segmentation consistency based on the degree of region overlap between clusters
Boundary Displacement Error (BDE) [117]	Computes the average displacement error between the boundary pixels of a segmented image S and their closest corresponding boundary pixels found in the GT image
Variation of Information (VI) [118]	Computes the conditional entropies between the class label distributions of the result S and the GT data
Rand Index (R) [124]	Calculates the normalised sum of the pairs of pixels that have the same label relationship in both the segmented result and the GT image
Probabilistic Rand Index (PR) [119]	The PR Index compares the segmented result against a set of GT images by evaluating the relationships between pairs of pixels as a function of variability in the ground-truth set
Normalised Probabilistic Rand (NPR) [61,120]	A modification of the PR Index that is normalised with respect to a baseline common to all images contained in the data set
Earth Mover Distance (EMD) [121,126]	EMD is given by the minimal cost needed to move all the individual points between the two evaluated distributions
Distance distribution signatures (D_B) [122]	A discrete function whose distribution characterises the distance discrepancies between the segmented boundary pixels and the GT boundary pixels. Statistics such as standard deviation, median or mean are calculated (e.g. small standard deviation indicates high segmentation quality)
Hamming distance [122]	The total area of overlap between all regions that belong to the GT and S. This measure is usually normalised
Precision (P) and recall (R)	P =fraction of boundary pixels from the segmented image that matches those in the GT data R =fraction of boundary pixels that belong to the GT data for which a match was found in the segmented image
F-measure [95,123]	A weighted harmonic mean of combined precision and recall values. Higher precision, recall and F-measure values indicate a better segmentation result
ROC curves [125]	Similar to the precision-recall curve, the ROC curve depicts the trade-off between the hit rate (recall) and the false alarm rate

Another possibility to evaluate the accuracy of the segmentation algorithms is to measure the difference between two segmentations by computing the Variation of Information (VI) metric [118]. VI is defined in terms of the conditional entropies between the class label distributions of the obtained result and the ground-truth data, but its use proved problematic when applied to evaluate the segmentation accuracy when more ground-truth images are generated for each image in the database.

The Precision-Recall curves and their weighted harmonic mean (*F*-measure) [123] evaluate the accuracy of the segmentation algorithms by computing the percentage of matched boundary pixels between the segmented result and the ground-truth image. These measures are usually used in the context of image retrieval, but Martin et al. [95] proposed to use them for the quantitative evaluation of the segmentation algorithms. The Precision (*P*) measure is given by the number of matched boundary pixels between the segmented result and the ground-truth image, divided by the total number of boundary pixels in the segmented image. The Recall (*R*) is calculated as the fraction of boundary pixels from the ground-truth data for which a match was found in the segmented image. Higher values of *P* and *R* indicate higher agreement between the boundary pixels in the segmented and ground-truth data. The recall measure has also been used to assess the level of under-segmentation [126]. One drawback in using the precision-recall curves is that they are not tolerant to refinement and it is possible that two segmentations that are good mutual refinements of each other to have low precision and recall scores [120]. Refinement occurs when two images are segmented in the same manner where the only difference being that in one of the images the objects are divided into smaller segments when compared to the other [95].

Similar to the precision-recall curve is the ROC (Receiver Operating Characteristics) curve [125] that plots the false alarm rate or specificity (defined as the probability that a true negative is labelled as a false positive) versus the recall values. However it is useful to note that the ROC curves are seldom employed to evaluate the performance of segmentation algorithms as they are

not appropriate measures to quantify a detected boundary [95]. As indicated in Table 1, other measures proposed in the literature to evaluate the accuracy of the segmentation process include: the Hamming Distance [122], Distance Distribution Signatures (D_B) [122], Earth Mover Distance (EMD) [121,126] and Boundary Displacement Error (BDE) [117].

The majority of these measures were designed to compare the segmented result against only one ground-truth image. But in the case of natural and medical images the ground-truth generation involves a subjective user-defined procedure and as a result multiple ground-truth segmentations are obtained for each image when multiple users are involved in the manual annotation process. To adapt to this new performance evaluation scenario, the Probabilistic Rand (PR) and Normalised Probabilistic Rand (NPR) indexes were recently proposed to quantify the agreement between a segmented result and a set of manually annotated images. The PR Index [119] compares the segmented result against multiple ground-truth images by calculating soft non-uniform weights for each pair of pixels in the image as a function of the variability in the ground-truth set. If we assume that *S* is the segmented image that will be compared against the manually labelled set of ground-truth images $\{GT_1, GT_2, \dots, GT_Q\}$, where *Q* denotes the total number of manually segmented images, the segmentation result is quantified as appropriate if it correctly identifies the pairwise relationships between the pixels as defined in the ground-truth segmentations. In other words, the pairwise labels I_i^S and I_j^S (corresponding to any pair of pixels x_i, x_j in the segmented image *S*) are compared against the pairwise labels $I_i^{GT_Q}$ and $I_j^{GT_Q}$ in the ground-truth segmentations and vice versa.

Since the PR index has been often employed to analyse the performance of recently developed segmentation algorithms, we will provide details about its mathematical formulation

$$PR(S, \{GT_{1,\dots,Q}\}) = \frac{1}{\binom{N}{2}} \sum_{\substack{i,j \\ i \neq j}} [I(I_i^S = I_j^S)p_{ij} + I(I_i^S \neq I_j^S)(1-p_{ij})] \quad (1)$$

where N is the total number of pixels in the image, $I(l_i^S = l_j^S)$ denotes the probability that the pair of pixels x_i and x_j have the same label in S and p_{ij} represents the mean pixel pair relationship between the ground-truth images that are calculated as follows:

$$p_{ij} = \frac{1}{Q} \sum_{g=1}^Q I(l_i^{GT_g} = l_j^{GT_g}) \quad (2)$$

As illustrated in Eq. (1), the PR index takes values in the interval $[0,1]$ and a higher PR value indicates a better match between the segmented result and the ground-truth data (the PR index takes the value 0 when there are no similarities between the segmented result and the set of manual segmentations and it takes the value 1 when all segmentations are identical).

The NPR index [61,120] was designed with the purpose of improving the PR measure by normalising its value with respect to all images contained in the dataset, i.e. taking into consideration the variability across all ground-truth segmentations. The NPR index proved to be more sensitive when compared to the PR index and it can take both positive and negative values where a score higher than 0 is considered to be meaningful. One substantial disadvantage associated with the NPR index is the high computational overhead and this is the main reason that rendered this performance evaluation measure as impractical when dealing with datasets that consist of a large number of images.

3.2. Colour-texture segmentation databases and benchmarks

Several databases have been proposed by the computer vision community that consist of a large variety of colour-textured images that can be employed in the quantification of colour-texture segmentation algorithms.

In this regard, the McGill Calibrated Colour Image Database [127] has over 850 natural scenes with strong colour-texture characteristics that are divided into nine categories, namely flowers, animals, foliage, textures, fruits, landscapes, winter, manmade and shadows. Each of these categories contain between 48 and 304 images (resolution 786×576) that were captured with two Nikon Coolpix 5700 digital cameras. The McGill database provides a complex testing scenario for colour-texture segmentation, as it contains a large range of images that are characterised by inhomogeneities with respect to the texture and colour content. However, its drawback consists in the lack of ground-truth data which makes the evaluation of the segmentation algorithms problematic. Griffin et al. [128] from California Institute of Technology, proposed the Caltech-256 Object Category Dataset that contains 30,607 images that were acquired using Google and PicSearch web internet search engines. This database contains a wide variety of natural and artificial objects where each category has between 80 and 827 images. The Caltech-256 database has the same inconvenience as the McGill database, the absence of ground-truth data.

Often employed for texture evaluation is the MIT VisTex database [76] (Vision Texture – 1995, Massachusetts Institute of Technology) that contains both complex natural scenes and more than 100 real world individual textures. The VisTex textures (image resolution: 128×128 and 512×512) are divided into several categories including grass, water, canvas, brick, buildings and clouds and these texture prototypes have been widely used in research papers to build mosaic images that were employed to evaluate the performance of colour-texture segmentation algorithms. The use of VisTex texture prototypes to generate test data is appealing as the construction of mosaic images implies the existence of an objective ground-truth that facilitates the numerical evaluation of the segmentation algorithms. The Outex Texture Database [129] also proved popular with vision researchers as it provides a large collection of colour-textures (canvas, carpet,

wood, sand, tiles, etc.) that can be used for the empirical evaluation of both texture classification and segmentation algorithms. A related dataset is the CURET Database (Columbia-Utrecht Reflectance and Texture Database) [130] that contains a collection of 61 real-life complex colour-textures that are captured under various viewing and illumination directions. Another large collection of textures (The Texture Library) is available online at <http://textures.forrest.cz> and is divided into 17 categories of natural colour-textures with up to 153 images belonging to each category.

Pascal VOC 2009 Dataset [131] contains a total of 14,743 annotated colour images. Among these images there is a set of real-life scenes divided into 20 main categories including aeroplane, bicycle, bird, boat, horse, car, cat, bus, dog, person, etc. Each image in the set is provided with a manually labelled ground-truth segmentation. A large image database was built to evaluate the SIMPLcity image retrieval system proposed by Wang et al. [132]. The freely available database is divided into 10 categories where each category has 100 colour images describing different natural scenes: Africa people and villages, beach, building, busses, dinosaurs, elephants, flowers, horses, mountains and glaciers and food. These images were sampled from Corel database and are 384×256 pixels in size. Minerva (Machine Intelligence for Natural Environment Recognition and Visual Analysis) Scene Analysis Benchmark [133] contains 448 natural outdoor images in both colour and greyscale format collected from the University of Exeter campus. These images represent different natural scenes containing grass, trees, sky, clouds, pebbles, road and brick. The main drawback associated with this benchmark consists in the edge-detection driven methodology chosen to construct the ground-truth data.

In order to produce a baseline for the objective quantitative evaluation of different segmentation algorithms, Martin et al. [52] introduced the Berkeley Segmentation Dataset and Benchmark (BSDB). The freely available database contains 300 colour images covering a large variety of natural scenes and for each image is provided a set of ground-truth segmentations that were manually produced by multiple subjects. The BSDB images are 481×321 in size and were selected by the authors from the Corel Image Database, where the main selection criterion is that in each image there is at least one discernible object. The set of hand labelled images correspond to the variation in human perception of the scene under analysis. The Berkeley Dataset and Benchmark is widely used by the computer vision community and this interest is motivated by two reasons: (a) it consists of a large number of colour images that provides a complex testing scenario and (b) for each image between 5 and 8 ground-truth segmentations are provided that facilitate the numerical evaluation of the developed segmentation algorithms.

Recently, Haindl and Mikeš [134] introduced the Prague Texture Segmentation Data Generator and Benchmark. The authors noted that the manual annotations generated for natural images are affected by the human subjectivity, thus they proposed to construct synthetic (mosaic) scenes where the ground-truth data is unambiguous. To assist the user in the process of generating the synthetic scenes, the authors developed an algorithm based on the Voronoi polygon random generator that is employed in the construction of the mosaic images. The Prague colour-texture database consists of more than 1000 colour-textures and the generated textured mosaics are of six main types: monospectral, multispectral, BTF (Bidirectional Texture Function), rotation invariant, scale invariant and illumination invariant. The Prague dataset is freely available and allows the user to evaluate new segmentation algorithms and compare their performance with those obtained by the state of art algorithms using 27 different evaluation measures including the F -measure, LCE, GCE and VI.

A summary of the databases that are commonly employed in the process of evaluating the performance of colour-texture

algorithms is provided in Table 2. In this table we have also included the reference paper (whenever this is applicable) and the web address where the colour–texture image databases and benchmarks can be accessed.

3.3. Performance evaluation of the state of the art colour–texture segmentation algorithms

In this section the performance of different state of the art algorithms in the field of colour–texture segmentation will be evaluated based on the results that were reported by the authors when using colour images from publicly available datasets. It is useful to note that the process of comparing different segmentation algorithms is a challenging task since different evaluation scenarios are often adopted by the authors. Such scenarios include the evaluation of the proposed algorithms using different databases, different metrics for performance assessment or different parameter tuning.

In Table 3 the performances of representative algorithms published in the literature are quantified where details such as the name of the database, the number of images employed in the evaluation and the metric used for quantification are provided. This table also summarises the purpose and application (where applicable) of each analysed algorithm and reveals the colour model chosen by the authors for image analysis. In case the reported results for a particular segmentation algorithm are evaluated based only on a visual examination, we will advise the reader to consult the original paper in order to obtain more details about the methodology used in the experimental activity.

As mentioned earlier, several issues emerge when analysing the results reported for different colour–texture segmentation algorithms. The first issue consists in the selection of different databases (sometimes chosen in conjunction with particular applications) and the variation in the number of images used for experimentation. In this regard, some authors preferred to use only selectively the image data contained in publicly available databases during performance evaluation. This scenario adds substantial complications when the performance of these techniques is contrasted with that achieved by other algorithms that were evaluated on the same database. The second factor resides in the selection of different performance measures for the numerical evaluation. In the past, the percentage of misclassified pixels was the most common measure employed to assess the performance of the developed algorithms, but recently metrics such as PR Index [119], VI [118], GCE [116] and BDE [117] have started to be used more widely to benchmark the performance of the algorithms on standard databases. The third factor is associated with the optimal selection of the parameters that control the behaviour of the developed algorithms. While the

robust selection of these parameters is often an important issue when the results of the research are reported, in Table 3 we have collated only the best results that were reported by the authors.

As it can be observed in Table 3, the state of the art technique that has been chosen by the majority of the authors for comparison purposes is JSEG that has been developed by Deng and Manjunath [34]. As indicated in [34], JSEG has three important parameters that need to be set by the user: the quantisation threshold, the scale and the merge parameter. When the segmentation algorithms proposed by different authors were compared against JSEG, the JSEG parameters were not always set to the same values (for example Chen et al. [63], adopted a “no merge” selection). Table 3 also indicates that the most commonly employed database in the evaluation of colour–texture segmentation algorithms is the Berkeley database [52], followed by VisTex [76]. VisTex has one major drawback when used to evaluate the performance of different algorithms. This is given by the fact that authors usually generate different mosaic images to evaluate the accuracy of the developed algorithms, thus the testing scenario is changed and as a result the reported comparisons are less relevant. While the survey provided in Table 3 is useful when evaluating the performance of a large spectrum of colour–texture segmentation algorithms, we should note that more efforts have to be devoted to the development of standard evaluation frameworks (databases and performance metrics) that should be used in the process of quantifying the accuracy of novel techniques. Based on the trends associated with the latest papers published in the field of colour–texture segmentation, we can note that the Berkeley database and the PR index are the most used dataset and performance metric for the quantitative evaluations of recent colour–texture segmentation algorithms.

4. Discussion and conclusion

The major objective of this paper was to analyse the main directions of research in the field of colour–texture segmentation and to categorise the main approaches with respect to the integration of the colour and texture descriptors in the segmentation process. After evaluating a large number of papers, we identified three major trends in the development of colour–texture segmentation, namely algorithms based on implicit feature integration, approaches that integrate the colour and texture attributes in succession and finally methods that extract the colour and texture features on independent channels and combine them using various integration schemes. As we discussed in Section 2 the methods that fall in the latter categories proved to be more promising when viewed from algorithmic and practical

Table 2

Publicly available databases containing images with colour–texture characteristics.

Database	Web address
<i>Berkeley Segmentation Dataset and Benchmark</i> (2001) [52]	http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/
McGill calibrated colour image database (2004) [127]	http://tabby.vision.mcgill.ca
Outex database (2002) [129]	http://www.outex.oulu.fi/
VisTex database (1995) [76]	http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html
Caltech-256 (2007) [128]	http://www.vision.caltech.edu/Image_Datasets/Caltech256/
<i>The Prague Texture Segmentation Data Generator and Benchmark</i> (2008) [134]	http://mosaic.utia.cas.cz/
Pascal VOC (updated 2009) [131]	http://pascallin.ecs.soton.ac.uk/challenges/VOC/voc2009/#devkit
CURet (1999) [130]	http://www.cs.columbia.edu/CAVE/software/curet/
SIMPLcity (2001) [132]	http://wang.ist.psu.edu/docs/related/
Minerva (2001) [133]	http://www.paaonline.net/benchmarks/minerva/
The Texture Library Database (updated 2009)	http://textures.forrest.cz
BarkTex (1998) [135]	ftp://ftphost.uni-koblenz.de/outgoing/vision/Lakmann/BarkTex
Corel	Commercially available
VxC Tiles surface grading [136]	http://miron.disca.upv.es/vision/vxctsg/

Benchmark datasets are marked in italics.

Table 3

Summary performance of colour–texture segmentation algorithms. The numerical results are those reported by the authors in the original papers.

Colour–texture algorithm	Dataset	No. of images	Evaluation measure (s)	Compared against	Reported numerical results (if available)					Purpose and application	Colour model(s)
Mirhmedi and Petrou [31]	VisTex [76]	27 mosaics	● % misclassified pixels (avg. error)	Edge flow [32]	● Proposed: 1.78% (mean value) ● Edge-Flow: 5.18% (mean value)					Perceptual CT Seg	O ₁ O ₂ O ₃ and CIE Luv
	–	4 natural	● visual		–						
B-JSEG (Wang et al. [35])	Berkeley [52]	150 random	Average % error	JSEG [34]	JSEG: 33.1%; B-JSEG: 24.1%; [39]: 24.3%; JSEG: 36.1%					CT Seg for natural images	CIE Luv
Yu et al. [39]	Berkeley	200	LCE [116]	JSEG [34]						CT Seg	Gaussian Colour Model
Hoang et al. [27]	Corel	40,000	Visual (10 examples)	–	–					CT Seg (natural and synthetic data)	Gaussian Colour Model
Chen et al. [63]	Berkeley	10 natural	Visual	JSEG [34]	–					CT Seg, CBIR	CIE Lab
CTM (Yang et al. [44])	Berkeley	300	PR [119], VI [118], GCE [116], BDE [117]	MS [41], NC [42], FH [43]	PR	VI	GCE	BDE	Unsupervised CT Seg (natural images)	CIE Lab	
					CTM _{$\gamma=0.1$}	0.75	2.46	0.17	9.42		
					CTM _{$\gamma=0.15$}	0.76	2.20	0.18	9.49		
					CTM _{$\gamma=0.2$}	0.76	2.02	0.18	9.89		
					MS	0.75	2.47	0.25	9.7		
					NC	0.72	2.93	0.21	9.60		
					FH	0.78	2.66	0.18	9.94		
MIS (Krinidis and Pitas [40])	Berkeley	300	PR [119], GCE [116], VI [118], BDE [117]	MS [41], NC [42], NNG [43], CTM [44]	PR	VI	BDE	GCE	CT Seg	RGB, CIE Luv	
					MIS	0.79	1.93	7.82	0.19		
					MS	0.75	2.47	9.70	0.25		
					NC	0.72	2.93	9.60	0.21		
					NNG	0.78	2.66	9.94	0.18		
					CTM _{$\gamma=0.1$}	0.75	2.46	9.42	0.17		
					CTM _{$\gamma=0.15$}	0.76	2.20	9.49	0.18		
					CTM _{$\gamma=0.2$}	0.76	2.02	9.89	0.18		
HMC (Hedjam and Mignotte [50])	Berkeley	300	PR [119], VI [118], GCE [116], BDE [117]	FCR [138], CTM [44], MS [41], NC [42], FH(NNG) [43]	PR	VI	GCE	BDE	CT Seg	RGB, HSV, CIE Luv, YIQ, XYZ and CIE Lab	
					HMC	0.78	3.8	0.3	8.93		
					FCR	0.78	2.3	0.21	8.99		
					CTM _{$\gamma=0.1$}	0.75	2.46	0.17	9.42		
					CTM _{$\gamma=0.2$}	0.76	2.02	0.18	9.89		
					MS	0.75	2.47	0.25	9.7		
					NC	0.72	2.93	0.21	9.60		
					FH	0.78	2.66	0.18	9.94		
Nammalwar et al. [57]	VisTex [76]	46, mosaics and natural	Mean error	–	4.53					CT Seg	RGB
(GSEG) Ugarriza et al. [59]	Berkeley	300	Peak (<i>p</i>) of the NPR distributions	JSEG [34], GRF [60]	NPR _{p,GSEG} =0.8; NPR _{p,JSEG} =0.7; NPR _{p,GRF} =0.55;					Segmentation of natural images	CIE Lab
Freixenet et al. [67]	VisTex [76]	9 mosaics	● % misclassified pixels, distance of boundary displacement;	–	% error distance					CT Seg	CIE Luv
	Jolly and Gupta [100]	3 mosaics	● Visual		<i>m</i>	2.218	0.841				
	–	6 natural			σ	1.711	0.940				
	–	5			–						
Sail-Allili and Ziou [68]	Corel	5	LCE [116]	Blobworld [98], Mansoursi et al. [139]	[68]: LCE=0.11(mean); Blobworld: LCE=0.25 (mean); Mansoursi: LCE=0.22 (mean);					CT Seg	CIE Lab
AC (Luis-Garcia et al. [69])	CUReT [130]	100 mosaics	Percentiles success score, aggregated Area Under Curve (AUC)	CLST [141], Bouman and Shapiro [140], Hoang [27]	AC: AUC=0.21; CLST: AUC=0.31; [138]: AUC=0.34; [27]: AUC=0.38;					CT Seg	RGB
	–	7 natural	–	–	–						
UGC (Kim and Hong) [75]	VisTex	6 mosaics	Precision-recal, <i>F</i> -measure (avg)	JSEG [34]	JSEG: <i>F</i> -measure=0.67; UGC: <i>F</i> -measure=0.92; JSEG: <i>F</i> -measure=0.44; UGC: <i>F</i> -measure=0.57;					CT Seg	RGB
	Berkeley	24									

Table 3 (continued)

Colour–texture algorithm	Dataset	No. of images	Evaluation measure (s)	Compared against	Reported numerical results (if available)	Purpose and application	Colour model(s)																				
CTex (Ilea and Whelan) [80]	Berkeley	300	PR Index [119]	JSEG [34]	CTex: PR=0.80; JSEG: PR=0.77;	CT Seg	RGB, YIQ																				
	VisTex and Photoshop mosaics	33 mosaics	m , σ , rms of the boundary displacement error		<table><tr><td></td><td>m</td><td>σ</td><td colspan="2">rms</td></tr><tr><td>CTex</td><td>0.95</td><td>0.97</td><td colspan="2">1.38</td></tr><tr><td>JSEG</td><td>2.68</td><td>4.20</td><td colspan="2">5.01</td></tr></table>		m	σ	rms		CTex	0.95	0.97	1.38		JSEG	2.68	4.20	5.01								
	m	σ	rms																								
CTex	0.95	0.97	1.38																								
JSEG	2.68	4.20	5.01																								
Martin et al. [95] (BG+CG+TG)	Berkeley	300	GCE [116], F -measure @ (precision, recall)	CD-H, 2MM (see [95])	CD-H: 0.61@(0.70, 0.55); 2MM: 0.63@(0.71, 0.57); (BG+CG+TG): 0.70@(0.75, 0.66); Distance_tolerance=3.2; 100 test images: 0.67; 200 training images: 0.69;	Boundary detection in natural scenes	CIE Lab																				
Luo and Khoshgoftaar [142]	Berkeley [52]	200 training 100 test	F -measure	–	–	Image segmentation	CIE Luv																				
Shi and Funt [28]	–	12 images	Visual	–	–	CT Seg (natural)	RGB																				
Wang et al. [29]	VisTex	2 mosaics 3 natural	Visual	–	–	CT Seg	IHS																				
Khan et al. [101]	Berkeley	13	Hit rate	–	97–99%	CT Seg (natural)	CIE Lab																				
Han et al. [73]	Berkeley	17	Visual	GrabCut [72]	–	Natural image segmentation	RGB, CIE Lab																				
Kato and Pong [105]	VisTex	4 mosaics (I_1, \dots, I_4); 2 natural	% Misclassified pixels	JSEG	$I1$: 5.85; $I2$: 2.76; $I3$: 0.8; $I4$: 24.6; (I_n =mosaic image n);	CT Seg	CIE Luv																				
JSEG (Deng and Manjunath [34])	Corel Photos	2500	Visual Visual and error rate (for 2 images only)	–	–	CT Seg	CIE Luv																				
Chen and Chen [56]	VisTex	35 mosaics	Error rate graph (m , σ of the error)	–	Image 1: 1.99% Image 2: 2.09% m_{\min} =0.023; m_{\max} =0.066; σ_{\min} =0.05; σ_{\max} =0.175;	CT Seg, CBIR	HSV, RGB																				
Gevers [45]	Images of Amsterdam	4 natural 600	Visual Precision-recall curves	Histogram intersection	– See [45]	CBIR	RGB																				
Campbell and Thomas [85]	Bristol Database [137]	80	Area overlap	–	Average _{area_overlap} =62.2%	CT Seg of artificial and natural scenes	Opponent Colour Representation																				
Edge-Flow [32]	Corel database	2500	Visual	–	–	Image segmentation	RGB																				
Hanbury and Marcotegui (WF and WS) [97]	Berkeley	300	GCE, F -measure	NC [42]	<table><tr><td></td><td>GCE</td><td>F-measure</td></tr><tr><td>WF:</td><td>0.19</td><td>0.44</td></tr><tr><td>WS:</td><td>0.22</td><td>0.55</td></tr><tr><td>NC:</td><td>0.23</td><td>0.48</td></tr></table>		GCE	F -measure	WF:	0.19	0.44	WS:	0.22	0.55	NC:	0.23	0.48	CT Seg. (natural)	CIE Lab								
	GCE	F -measure																									
WF:	0.19	0.44																									
WS:	0.22	0.55																									
NC:	0.23	0.48																									
Blobworld (Carson et al. [98])	Corel photos	10,000	Precision-recall curves	–	See [98]	CBIR	CIE Lab																				
Ozden and Polat [143]	Berkeley, others	8	Error rate	MS [41]	$mean_{\%error-proposed}$ =5.75% $mean_{\%error-MS}$ =11.75%	Image segmentation	CIE Luv																				
CTREG (Fondon et al. [65])	–	10 mosaics	Precision (P) Recall (R)	–	<table><tr><td></td><td>P_{mean}</td><td>P_{σ}</td><td>R_{mean}</td><td>R_{σ}</td></tr><tr><td>CTREG:</td><td>0.94</td><td>0.04</td><td>0.98</td><td>0.0003</td></tr><tr><td>CTREG:</td><td>0.81</td><td>0.21</td><td>0.69</td><td>0.19</td></tr><tr><td>Blobworld:</td><td>0.63</td><td>0.31</td><td>0.68</td><td>0.21</td></tr></table>		P_{mean}	P_{σ}	R_{mean}	R_{σ}	CTREG:	0.94	0.04	0.98	0.0003	CTREG:	0.81	0.21	0.69	0.19	Blobworld:	0.63	0.31	0.68	0.21	CT Seg	CIE Lab
	P_{mean}	P_{σ}	R_{mean}	R_{σ}																							
CTREG:	0.94	0.04	0.98	0.0003																							
CTREG:	0.81	0.21	0.69	0.19																							
Blobworld:	0.63	0.31	0.68	0.21																							
PRIF (Mignotte [144])	Berkeley [52]	300 images: ● Test: 100 ● Train: 200	PR Index [119], F -measure	FH [43], FCR [138], CTex [80], JSEG [34], CTM [44], MS [41], NC [42]	PRIF: PR Index=0.80; F -measure calculated for the: Train set: 0.64@(0.63, 0.66) Test set: 0.63@(0.62, 0.63) (best results are presented)	Image segmentation	10 different colour spaces																				

The abbreviations used in the table can be translated as follows: CT Seg=Colour–Texture Segmentation; UGC=Unsupervised Graph Cuts; GSEG=Gradient SEGmentation (segmentation by dynamic region growth and multi-resolution merging); GRF=colour and edge information for segmentation and edge-linking; JSEG=J-Image SEGmentation; MIS=Modal Image Segmentation; MS=Mean-Shift; NC=Normalised Cuts; NNG=Nearest Neighbour Graphs (Felzensawalb and Huttenlocher); CTM=Compression based Texture Merging; HMC=Hierarchical Markov Clustering; FCR=Fusion for Clustering Results; WF=Waterfall; WS=Watershed using volume extension; (BG+CG+TG)=(brightness gradient+colour gradient+texture gradient); CD-H=Canny edge detector with hysteresis; 2MM=2nd Moment Matrix; CBIR=Content-Based Image Retrieval; AC=Adaptive Combined Colour–texture Segmentation [69]; CLST=Compact Local Structure Tensor; CTREG=Colour and Texture Region Growing; PRIF [144]=Probabilistic Rand Index Fusion; Error rate=number of misclassified pixels/total number of pixels in the image; σ =standard deviation; m =mean; Success score=number of pixels correctly classified/total number of pixels.

perspectives. However, since the level of algorithmic sophistication and the application domain of the newly proposed algorithms is constantly increasing it is very difficult to predict which approach will dominate the field of colour–texture analysis in the medium to long term but we believe that the next generation of algorithms will attempt to bridge the gaps between approaches based on sequential feature integration and those that extract the colour–texture features on independent channels. Currently, the main research area in the field of colour–texture segmentation is focused on methods that integrate the features using statistic/probabilistic schemes and methods based on energy minimisation. However in line with the development of new algorithms an important emphasis should be placed on methodologies that are applied to evaluate the performance of the image segmentation algorithms. We feel that this issue had not received the attention that it should deserve and as a result the lack of widely accepted metrics by the computer vision community made the task of evaluating the appropriateness of the developed algorithms extremely difficult. Although substantial work needs to be done in the area of performance evaluation, it is useful to mention that most of the algorithms that have been recently published had been evaluated on standard databases and using well-established metrics. Also, it is fair to mention that the publicly available datasets are not sufficiently generic to allow a comprehensive evaluation, but with the emergence of benchmark suites such as Berkeley database this issue starts to finally find an answer.

We believe that this review has thoroughly sampled the field of colour–texture segmentation using a systematic evaluation of a large number of representative approaches with respect to feature integration and has also presented a useful overview about past and contemporary directions of research. To further broaden the scope of this review, we have also provided a detailed discussion about the evaluation metrics, we examined the most important data collections that are currently available to test the image segmentation algorithms and we analysed the performance attained by the state of the art implementations. Finally, we cannot conclude this paper without mentioning the tremendous development of this field of research during the past decade and due to the vast spectrum of applications, we predict that colour–texture analysis will remain one of the fundamental research topics in the foreseeable future.

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