Electronic Letters on Computer Vision and Image Analysis 7(3):1-22, 2008

A Review of Recent Advances in Surface Defect Detection using Texture analysis Techniques

Xianghua Xie

Department of Computer Science, University of Wales Swansea, Swansea SA2 8PP, United Kingdom

Received 10th october 2007; revised 29th march 2008; accepted 18th april 2008

Abstract

In this paper, we systematically review recent advances in surface inspection using computer vision and image processing techniques, particularly those based on texture analysis methods. The aim is to review the state-of-the-art techniques for the purposes of visual inspection and decision making schemes that are able to discriminate the features extracted from normal and defective regions. This field is so vast that it is impossible to cover all the aspects of visual inspection. This paper focuses on a particular but important subset which generally treats visual surface inspection as texture analysis problems. Other topics related to visual inspection such as imaging system and data acquisition are out of the scope of this survey.

The surface defects are loosely separated into two types. One is local textural irregularities which is the main concern for most visual surface inspection applications. The other is global deviation of colour and/or texture, where local pattern or texture does not exhibit abnormalities. We refer this type of defects as shade or tonality problem. The second type of defects have been largely neglected until recently, particularly when colour imaging system has been widely used in visual inspection and where chromatic consistency plays an important role in quality control. The emphasis of this survey though is still on detecting local abnormalities, given the fact that majority of the reported works are dealing with the first type of defects.

The techniques used to inspect textural abnormalities are discussed in four categories, statistical approaches, structural approaches, filter based methods, and model based approaches, with a comprehensive list of references to some recent works. Due to rising demand and practice of colour texture analysis in application to visual inspection, those works that are dealing with colour texture analysis are discussed separately. It is also worth noting that processing vector-valued data has its unique challenges, which conventional surface inspection methods have often ignored or do not encounter.

We also compare classification approaches with novelty detection approaches at the decision making stage. Classification approaches often require supervised training and usually provide better performance than novelty detection based approaches where training is only carried out on defect-free samples. However, novelty detection is relatively easier to adapt and is particularly desirable when training samples are incomplete.

Key Words: Surface Inspection, Defect Detection, Novelty Detection, Texture Analysis.

Correspondence to: <x.xie@swansea.ac.uk>

Recommended for acceptance by David Fofi and Ralph Seulin
ELCVIA ISSN:1577-5097
Published by Computer Vision Center / Universitat Autònoma de Barcelona, Barcelona, Spain

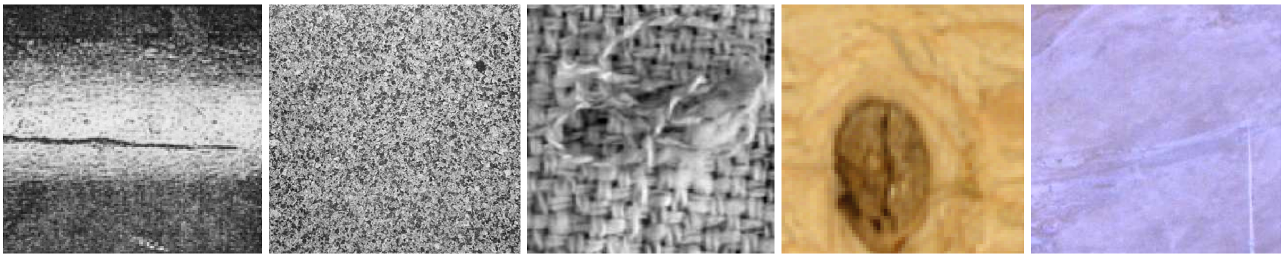

Figure 1: Example defects on different types of surfaces - from left: Steel [109], stone [72], textile [116], wood [122], and ceramic tiles [149].

1 Introduction

Non-destructive visual inspection for texture and/or colour abnormalities has application on a variety of surfaces e.g. wood, steel, wafer, ceramics, and even non-flat objects such as fruits and aircraft surfaces, and is highly demanded by industry in order to replace the subjective and repetitive process of manual inspection. For example, in ceramic tile production, chromato-textural properties of the final product can be affected by a variety of external factors that are difficult to control, such as colour pigments, humidity, and temperature. Thus, online monitoring and feedback control of the whole production line becomes desirable.

There are numerous reported works in the past two decades during which computer vision based inspection has become one of the most important application areas. Chin [22] and Newman and Jain [93] provided a comprehensive overview of surface inspection in late eighties and mid nineties, respectively. Recently, Li and Gu [69] surveyed recent advances in free form surface inspection. However, there have been significant advances in all aspects of surface inspection using computer vision in the recent years. There are also newly emerging topics such as tonality inspection and increasing use of colour imaging devices which requires algorithms efficiently deal with vector-valued data. This paper focuses on the recent developments in vision based surface inspection using image processing techniques, particularly those that are based on texture analysis methods.

The visual inspection process often involves texture and/or colour analysis and pattern classification (decision making). The former is mainly concerned with feature representation and extraction, as well as data perception and modelling. The latter consists of pattern representation, cluster analysis, and discriminant analysis. We discuss the texture feature extraction and analysis in four categories, namely statistical approaches, structural approaches, filter based methods, and model based approaches. A categorised list of representative works are given as pointers to these methods discussed in this paper. Some recent applied comparative studies are also reviewed. However, it is worth noting that surface inspection using texture analysis should not be considered the same as general texture segmentation and classification. Both defect-free and defective areas of inspected surfaces can be texturally unstationary, i.e. they will be often further segmented into smaller regions while in defect detection the defective region should be treated as a whole no matter how unstationary it is. Classifying surfaces into defect-free and defective is also different from texture classification, as defective samples are not necessary form a single class and the defect types may only be partially predicated beforehand. Additionally, in some applications false positives (rejecting good samples) is more forgivable than false negative (missing defective regions or samples).

A significant differentiating factor in visual inspection approaches is that of supervised classification versus novelty detection. For applications where both normal and defective samples can be easily obtained and pre-defined, supervised classification based approaches are usually favoured. However, when defects are unpredictable and defective samples are unavailable, novelty detection is more desirable. Both of these approaches will be reviewed and compared in the context of defect detection.

Aside from inspecting textural faults, inspecting tonality defects in terms of overall visual impression is also a significant production quality factor. The variation of overall colour or textural characteristics from surface to surface is known as the tonality problem. Any changes in the tonality, however subtle, will still become

Table 1: Inexhaustive list of textural defect detection methods

Approach	**Method**	**References**
Statistical	1. Histogram properties	[58, 133, 57, 96, 94]
	2. Co-occurrence matrix	[30, 121, 48, 10, 120, 101, 47, 66]
	3. Local binary pattern	[47, 96, 95, 79, 80]
	4. Other graylevel statistics	[21, 118, 131, 61, 23]
	5. Autocorrelation	[145, 46]
	6. Registration-based	[73, 143, 32, 146]
Structural	1. Primitive measurement	[60, 123]
	2. Edge Features	[142]
	3. Skeleton representation	[19]
	4. Morphological operations	[60, 123, 82]
Filter based	1. Spatial domain filtering	[2, 137, 92, 154, 101, 64, 39, 90]
	2. Frequency domain analysis	[113, 151, 20, 37, 127, 18, 129]
	3. Joint spatial/spatial-frequency	[17, 52, 38, 59, 117, 144, 66, 62, 132, 128, 112, 152, 9, 63, 6, 89, 84, 119, 153, 130, 72]
Model based	1. Fractal models	[28, 29]
	2. Random field model	[26, 102, 101, 5, 108]
	3. Texem model	[149]
Colour texture analysis for defect detection		[60, 123, 131, 80, 122, 39, 130, 149]

significant once the surfaces are placed together. The problem is compounded when the surface of the object is not just plain-coloured, but highly textured. In applications like tile production it is important to maintain the tonality consistency.

The rest of the paper is organised as follows. As the techniques reviewed in textural defect detection generally include those that have been used in tonality inspection, textural defect detection and related texture analysis techniques are first discussed in Section 2. Tonality inspection is then reviewed later in Section 3. The ability for a texture analysis technique to be extendible to deal with colour images is particularly important for applications using colour imaging. Thus, colour texture analysis is separately discussed in Section 4. Section 5 compares classification oriented approaches with novelty detection based approaches. Finally, Section 6 summaries this paper.

2 Textural Defect Detection

Texture is one of the most important characteristics in identifying defects or flaws. Fig. 1 shows some example defects in different types of material. It provides important information for recognition and interpolation. In fact, the task of detecting defects has been largely viewed as a texture analysis problem. Features with large inter-class variations and small intra-class variations are sought to better separate differing textures. Much effort has been put into extracting useful texture features. As it is not practical to provide an exhaustive survey of all texture features, this section concentrates on those techniques that have been widely used in texture analysis or demonstrate good potential for application to automatic inspection.

With reference to several texture analysis survey papers [43, 141, 138, 140, 114, 134], we categorise texture analysis techniques used for visual inspection four ways: statistical approaches, structural approaches, filter based approaches, and model based approaches. As already noted, colour texture analysis is separately discussed later. Table 1 shows a summary list of some of the key texture analysis methods that have been applied to defect detection. Clearly, statistical and filter based approaches have been very popular.

2.1 Statistical approaches

Statistical texture analysis methods measure the spatial distribution of pixel values. They are well rooted in the computer vision world and have been extensively applied to various tasks. A large number of statistical texture features have been proposed, ranging from first order statistics to higher order statistics. Amongst many, histogram statistics, co-occurrence matrices, autocorrelation, and local binary patterns have been applied to visual inspection.

2.1.1 Histogram properties

Commonly used histogram statistics include range, mean, geometric mean, harmonic mean, standard deviation, variance, and median. Histogram comparison statistics, such as L_1 norm, L_2 norm, Mallows or EMD distance, Bhattacharyya distance, Matusita distance, Divergence, Histogram intersection, Chi-square, and Normalised correlation coefficient, can also be used as texture features.

Despite their simplicity, histogram techniques have proved their worth as a low cost, low level approach in various applications, such as [124, 13, 111]. They are invariant to translation and rotation, and insensitive to the exact spatial distribution of the colour pixels. These characteristics make them ideal for use in application to tonality discrimination, e.g. [13, 150]. The accuracy of histogram based methods can be enhanced by using statistics from local image regions [15, 150]. Simple histogram moments, such as mean and standard deviation, from subblocks were used for defect classification [133]. Recently, Ng [94] proposed a histogram separation technique based on the Otsu global thresholding method [100] to segment surface defects. However, it requires the assumption that intensity of defective regions are separatable from those of normal regions which is not always true for textured surface.

2.1.2 Co-occurrence matrices

Spatial graylevel co-occurrence matrices (GLCM) [44] are one of the most well-known and widely used texture features. These second order statistics are accumulated into a set of 2D matrices, each of which measures the spatial dependency of two graylevels, given a displacement vector. Texture features, such as energy, entropy, contrast, homogeneity, and correlation, are then derived from the co-occurrence matrix. Several works have reported using co-occurrence matrices to detect defects, such as [30, 121, 133, 48, 10]. For example in [48], Iivarinen *et al.* applied co-occurrence texture features to detecting defects in paper web where the normal textures have characteristic frequency.

Co-occurrence matrix features can suffer from a number of shortcomings. It appears there is no generally accepted solution for optimising the displacement vector [134, 89]. The number of graylevels is usually reduced in order to keep the size of the co-occurrence matrix manageable. It is also important to ensure the number of entries of each matrix is adequate to be statistically reliable. For a given displacement vector, a large number of features can be computed, which implies dedicated feature selection procedures. In a comparative study by Özdemir *et al.* in [101], the co-occurrence matrix method showed poor performance in detecting textural defects in textile products compared to other techniques such as MRF and filtering-based methods. Iivarinen [47] found co-occurrence matrices and the local binary pattern (LBP) operator had similar performance in detecting defects, while LBP was more efficient.

2.1.3 Autocorrelation

The autocorrelation feature is derived based on the observation that some textures are repetitive in nature, such as textiles. It measures the correlation between the image itself and the image translated with a displacement vector. Textures with strong regularity will exhibit peaks and valleys in the autocorrelation measure. It is closely related to the power spectrum of the Fourier transform. This second order statistic can be sensitive to noise interference. Higher order statistics, e.g. [31, 46], have been investigated, for example, Huang and Chan [46] used fourth-order cumulants to extract harmonic peaks and demonstrated its ability to localise defects in textile images and Wood [145] used autocorrelation of subimages to detect textile defects. Nevertheless, the autocorrelation function is generally considered as unsuitable for random textures with irregularly arranged textural elements.

2.1.4 Local binary patterns

The LBP operator was first introduced by Ojala *et al.* [98] as a shift invariant complementary measure for local image contrast. It uses the graylevel of the centre pixel of a sliding window as a threshold for surrounding neighbourhood pixels. Its value is given as a weighted sum of thresholded neighbouring pixels. Usually, a simple local contrast measurement is calculated as a complement to the LBP value in order to characterise local spatial relationships, together called LBP/C [98]. Two-dimensional distributions of the LBP and local contrast measures are used as texture features.

The LBP operator is relatively invariant with respect to changes in illumination and image rotation (for example, compared to co-occurrence matrices), and computationally simple [78]. It has been applied to defect detection on ceramic tile surfaces [89], wood [96, 95], and real-time inspection [79]. Although good performance in texture classification has been achieved [99], LBP has been reported as considerably lower performance than co-occurrence matrix and filtering based approaches in detecting textural defects on ceramic tile surfaces, on which textures are usually randomly applied [89].

2.2 Structural approaches

In structural approaches, texture is characterised by *texture primitives* or texture elements, and the spatial arrangement of these primitives [140]. Thus, the primary goals of structural approaches are firstly to extract texture primitives, and secondly to model or generalise the spatial placement rules. The texture primitive can be as simple as individual pixels, a region with uniform graylevels, or line segments. The placement rules can be obtained through modelling geometric relationships between primitives or learning statistical properties from texture primitives.

In [19], Chen and Jain proposed a structural approach to identify defects in textile images. The image was first thresholded using histogram analysis and then was mapped into a data structure which represents the skeleton structure of the texture. Statistical measurements were taken from both location and length histograms of the skeleton. These measurements were compared with a pre-defined acceptance range which was learnt from defect-free samples to detect defects. Kittler *et al.* [60, 123] used K-means clustering to split randomly textured tile images into binary stacks, in which blob analysis was performed to measure the primitives. The measurements included size, perimeter fractality, elongatedness, and spatial distribution. In [82], the authors applied morphological operations to highlight defects in fabrics. Wen and Xia [142] performed leather surface defect detection by extracting edge segments and statistically evaluating those edges, for example, based on their length and strength.

2.3 Filter based approaches

The techniques reviewed in this section largely share a common characteristic, which is applying filter banks on the image and compute the energy of the filter responses. The methods can be divided into spatial domain, frequency domain, and joint spatial/spatial-frequency domain techniques.

2.3.1 Spatial domain and frequency domain filtering

Measuring edge strength and edge frequency is one of the earliest attempts to discriminate different textures. In the spatial domain, the images are usually filtered by gradient filters to extract edges, lines, isolated dots, etc. Sobel, Robert, Canny, Laplacian, Deriche, Laws filters have been routinely used as a precursor to measuring edge density. In [81], Malik and Perona designed a bank of differences of offset Gaussian function filters to model pre-attentive texture perception in human vision. Ade [1] proposed eigenfilters, a set of masks obtained from the Karhunen-Lóeve (KL) transform [54] of local image patches, for texture representation.

In [64], Kumar and Pang used linear finite impulse response (FIR) filters to detect defects in textiles. Filter responses from both defect free and defective regions were collected. Then, optimal filters were selected based on discriminant analysis of the filters using objective functions, such as Mahalanobis-Singh and Fisher criterion. Neubauer [92] exploited three 5×5 FIR filters and performed classification using histograms of features calculated from 10×10 pixel regions. Zhou *et al.* used simple linear filters to capture line-like defects in IC packages. Unser and Ade [137] and recently Monadjemi *et al.* [90] employed eigenfilters in defect detection. The authors argued that unlike other spatial operators, eigenfilters are image dependent and the detailed images are orthogonal to each other.

Many other methods apply filtering in the frequency domain, particularly when no straightforward kernel can be found in the spatial domain. The image is transformed into the Fourier domain, multiplied with the filter function and then re-transformed into the spatial domain saving on the spatial convolution operation. Ring and wedge filters are some of the most commonly used frequency domain filters. In [25], Coggins and Jain used seven dyadically spaced ring filters and four wedge-shaped orientation filters, which have Gaussian cross sections, for feature extraction. D'Astous and Jernigan [33] used peak features, such as strength and area, and power distribution features, such as power spectrum eigenvalues and circularity, to discriminate textures.

In [127], the authors used the Fourier transform to reconstruct textile images for defect detection. The line patterns in a textile image, supposed to be defects, were taken out by removing high energy frequency components in the Fourier domain using a one-dimensional Hough transform. The differences between the restored image and the original image were considered as potential defects. A similar idea was explored in [129], but low pass filtering was used to remove the periodic information. Chan and Pang [18] extracted harmonic peaks from horizontal and vertical power spectrum slices, based on the observation that defects usually occur in horizontal and vertical directions. However, these methods all rely on the assumption that faultless fabric is a repetitive and regular texture. These methods will not be suitable for defect detection in random textures.

2.3.2 Joint spatial/spatial-frequency methods

Since the Fourier coefficients are depending on the entire image, the Fourier transform is not able to localise the defective regions in the spatial domain. The classical way of introducing spatial dependency into Fourier analysis is through the windowed Fourier transform. If the window function is Gaussian, the windowed Fourier transform becomes the well-known Gabor transform, which can arguably achieve optimal localisation in the spatial and frequency domains [34]. Psychophysiological studies, such as [35], have suggested that the human brain performs multi-channel, frequency and orientation analysis on the visual image. These findings have strongly motivated the use of Gabor analysis, along with other multiscale techniques. Turner [135] and Bovik *et al.* [24] first proposed the use of Gabor filters in texture analysis. Jain and Farrokhnia [49] used it in segmentation and classification of textures with dyadic coverage of the radial spatial frequency range.

The Gabor filter bank has been extensively studied in visual inspection, e.g. [38, 144, 62, 132, 9, 63, 6, 89, 130]. Kumar and Pang [62] performed fabric defect detection using only real Gabor functions. Later in [63], the same authors used a class of self-similar Gabor functions to classify fabric defects. They also investigated defect detection using only imaginary Gabor functions as an edge detector. For computational efficiency, the fabric samples were analysed using horizontally and vertically projected one-dimensional profiles. In [9], Bodnarova *et al.* applied a Fisher cost function to select a subset of Gabor functions based on the mean and standard deviation of the template (defect-free) feature images to perform textile flaw detection. The filtering responses of those selected Gabor functions were supposed to have compact distributions. Defects were localised by thresholding the filtering responses from an unseen image sample based on the mean and standard deviation of template filtering responses. Tsai and Wu [132] also performed Gabor filter selection so that the filter response energy of the normal texture, assumed to be homogeneous, was close to zero. Wiltschi *et al.* [144] performed automatic scale selection to preserve channels with maximum energy and directional information. In [38], Escofet *et al.* performed multiscale Gabor filtering in a novelty detection framework. Defect candidates across different scales and orientations were fused together using logical processes.

Havig similar properties to the Gabor transform, wavelet transform representations have also been widely used for defect detection, e.g. defect detection and localisation[52, 59, 117, 66, 128, 112, 152, 84, 119, 153, 72]. Wavelet analysis uses approximating functions that are localised in both spatial and spatial-frequency domain. The input signal is considered as the weighted sum of overlapping wavelet functions, scaled and shifted. These functions are generated from a basic wavelet (or mother wavelet) by dilation and translation. The spatial resolution of wavelet transform is adapted to its frequency content, unlike in Gabor transform the spatial resolution is constant. In [117], Sari-Sarraf and Goddard performed discrete wavelet transforms on fabric images. The detailed images were fused together to produce a feature map in which the normal texture regions, assumed to be homogeneous, had small values. The defects were segmented by thresholds learnt from training templates. The key process was to attenuate the normal regions, and accentuate the defective regions, based on the assumption that normal texture was regular and homogeneous, and defects were those that broke the local homogeneity. Scharcanski [119] also used the discrete wavelet transform to classify stochastic textile textures. Rather using fixed dyadic scales, Kim *et al.* [59] employed a learning process to choose the wavelet scales for maximising the detectability of fabric defects. Latif-Amet *et al.* [66] extracted co-occurrence and MRF-based features from wavelet transform coefficients for fabric defect detection. Graylevel difference-based features from subbands of the wavelet transform were also applied in classifying fabric defects. Recently, Yang *et al.* [153] used adaptive wavelets resulting in fewer scales compared with the standard wavelet transform. The wavelet functions were adaptively selected based on an objective function measuring the ratio of average energies between defective regions and defect-free regions. The method achieved better performance than the standard wavelet transform, but needed supervised training. Wavelet frames [136] and image reconstruction techniques using wavelets were also used for defect detection [152, 128]. Recently, in [71] Lin used the one-level Harr wavelet transform to decompose surface barrier layer chip images and extracted wavelet features from normal samples and testing samples were statistically compared based on Hotelling, Mahalanobis, and Chi-square distances to detect ripple defects. The experimental results showed that Hotelling and Mahalanobis measures were superior in detecting those ripple defects than Chi-square testing. Very recently, Truchetet and Laligant [126] gave a very detailed review on wavelet analysis in industrial applications.

2.4 Model based approaches

Model based methods include, among many others, fractal models [83], autoregressive models [85, 27], random field models [68], the epitome model [53], and the texem model [149].

Fractals, initially proposed by Mandelbrot [83], are geometric primitives that are self-similar and irregular in nature. Fragments of a fractal object are exact or statistical copies of the whole object and they can match the whole by stretching and shifting. Fractal dimension and lacunarity are the most important measurements in fractal models. The former servs as a measure of complexity and irregularity; and the latter measures the structural variation or inhomogeneity. In [28, 29], Conci and Proenca used box counting to extract fractal features for detecting defects in fabric images. In a comparative study by Ohanian and Dubes [97], the fractal method performed reasonably well against co-occurrence matrices, Gabor filters, and Markov random fields in texture classification. However, it has achieved limited success in real applications. Fractals can have the same fractal dimension but look completely different. Fractal models are mainly suitable for natural textures where self-similarity may hold.

MRF theory provides a convenient and consistent way for modelling context dependent entities such as pixels, through characterising mutual influences among such entities using conditional MRF distributions [68]. The establishment of the equivalence between MRFs and Gibbs distribution [42, 8] provided tractable means for statistical analysis as Gibbs distribution takes a much simpler form.

In [26], Cohen *et al.* used Gaussian Markov Random Fields (GMRF) to model defect free textile web. The inspection process was treated as a hypothesis testing problem on the statistics derived from the GMRF model. The testing image was partitioned into non-overlapping sub-blocks, where each window was then classified as defective or non-defective. Baykut *et al.* [5] implemented this method in a real-time application with a dedicated DSP system. In [101], the authors showed that MRF based methods were competitive in a comparative study against other statistical and spectral based methods in defect detection.

Very recently, Xie and Mirmehdi [148, 147, 149] proposed a novel statistical model, called texture exemplars or texems, to represent and analyse random textures. In a two-layer structure, a texture image, as the first layer, is considered to be a superposition of a number of texture exemplars, possibly overlapped, from the second layer. Each texture exemplar, or simply texem, is characterised by mean values and corresponding covariances. Each set of these texems may comprise various sizes from different image scales. Different Gaussian mixture models were explored to learn these texem representations. Similar to the epitome model [53], only raw pixel values are used instead of filtering responses. However, unlike the epitome the texem model does not enforce the texture primitives condensing to a single image patch. The model was applied to localise defects on random textured ceramic tile surfaces and showed significant improvements compared against Gabor filtering based methods in a novelty detection framework.

2.5 Comparative studies

A classification of the texture analysis techniques used for defect detection is shown in Table 1. As mentioned earlier, the statistical and filter based methods have been in favour in terms of the amount of research reported. It is also worth noting that the categorisation of the texture analysis techniques used for defect detection as described above and listed in Table 1 is not a crisp classification. There are techniques that combine methods from different categories for texture analysis, e.g. [66] applies co-occurrence measurement on wavelet transformed detail images.

There are several comparative studies in the literature that evaluate texture analysis methods in application to defect detection. It must be noted that different studies use different datasets and possibly different parameter settings. Özdemir *et al.* [101] compared six texture features, consisting of MRF, KL transform, 2D Lattice filters, Laws filters, co-occurrence matrices, and a FFT-based method, for detecting textile defects. Texture modelling using a high (9th) order MRF model gave the best detection result. Iivarinen [47] demonstrated LBP and co-occurrence matrices features had similar performance in inspecting textured surfaces. Recently in [89], Monadjemi implemented three statistical (histogram-based, LBP, and co-occurrence matrices) and five signal processing schemes (Gabor filters, directional Walsh-Hadamard transform, discrete cosine transform, eigenfilters, and composition of Gabor filters) for randomly textured ceramic tile abnormality detection. The Gabor filter based composition scheme was found to be the most accurate method with good consistent performance across various tile types.

Although a solid conclusion can not be drawn to determine the best method for defect detection, it is clearly evident that filtering approaches, in particular Gabor filtering, have been more popularly applied in these areas (cf. Table 1). However, an attractive idea is to use local neighbourhood pixel relationships to model the texture, e.g. using methods based on the LBP, MRF, or the epitome and texem models. In fact, multi-channel filtering supports the claim that the joint distribution of neighbouring pixels determines texture appearance, as the joint distribution of pixel values in the filter support window determines the distribution of the filter response [67]. Notably, Varma and Zisserman [139] demonstrated better performance in texture classification using small neighbourhoods than using filter bank-based approaches. Representing texture using primitives is also effective, for example the texton representation. However, due to the difficulties in explicitly deriving

Figure 2: Example ceramic surfaces with three different chromatic tonalities (images from the authors of [75]).

primitive representation and associated displacement rules, there are relatively limited works using structural approaches (cf. Table 1).

As image textures may often contain both statistical and structural properties, a texture analysis method should be able to represent both types of properties in order to completely describe the texture [46]. Model-based texture analysis methods can generally represent both properties, e.g. [155]. Statistical models and their estimation have recently been an attractive topic, for example [53].

3 Tonality Inspection

In industrial quality inspection of colour textured surfaces, such as ceramic tiles or fabrics, it is also important to maintain consistent tonality during production. It is concerned with inspecting consistency among products regarding visual perception. Here, visual perception usually refers to chromatic, textural, or both appearance. Tonality variations, although subtle, can still be discernible once the surfaces are put together. This is therefore another important quality factor. Tonality inspection can be carried out on both uniform pattern surfaces and randomly textured surfaces, but manual detection is not only tiresome but rather difficult. Problems such as spatial and temporal variation of the illumination may introduce effects which make tonality grading even more difficult. There are clearly increasing research on this issue, e.g. [3, 77, 11, 12, 13, 14, 106, 4, 56, 74, 75, 76, 107].

In [4], Baldrich *et al.* segmented the tile image into several stacks using a K-means approach. Then statistical measures were used to represent local and global colour information and segment chromatic and shape characteristics of blobs within each stack. However, this was designed for a specific family of grainy tiles and may not be applicable to other types of randomly textured tiles. In [77], Lumbreras *et al.* used wavelet transforms to assess different colour channels and various decomposition schemes to find appropriate features in order to sort tiles into perceptually homogeneous classes. The feature vectors were classified to the nearest class by using Fisher's linear discriminant function. Similar work has been reported in [3], using wavelet analysis in RGB channels. The visual perception concerned with in these works, such as [4, 77, 3], include both textural and chromatic properties.

There are also scenarios in which consistency of chromatic characteristics are as predominantly important as for visual perception, for example [13, 74]. Fig. 2 gives such an example where three surfaces have three different chromatic tonalities with very subtle differences. Kauppinen [56] used RGB colour percentile features which were calculated from cumulative histograms to classify wood surfaces. Penaranda *et al.* [106] computed the first and second histogram moments of each channel of the RGB colour space as chromatic descriptors to classify tiles according to visual perception. Very recently, Lopez *et al.* [74, 75] used higher order histogram moments from each channel in $L^*a^*b^*$ colour space to characterise the colour tonality of ceramic tiles. In [11, 12], Boukouvalas *et al.* presented spatial and temporal constancy correction of the image illumination on the surfaces of uniform colour and two-colour (fix) patterned tiles. The luminance and the average colours in image channels, such as red, green, and blue, were used to perform tonality grading. Later in [13], the same authors proposed a colour histogram based method to automatically grade colour shade for randomly textured tiles by measuring the difference between the RGB histograms of a reference tile and each newly produced tile. By quantising the pixel values to a small number of bins for each band and employing an ordered binary tree, the 3D histograms were efficiently stored and compared. Several measures were investigated to perform the histogram comparison. Normalised cross correlation was found to be the most appropriate one as it gave the most consistent performance and also had a bounded range. This allowed the *a priori* definition of thresholds for colour tonality. In [14], the authors applied perceptual smoothing before colour tonality inspection. In [150], Xie and Mirmehdi further explored by incorporating local chromatic features to discriminate subtle colour tonality difference. These studies suggested that global measurements, particularly colour histograms and their related statistics are useful in colour tonality defect detection. Smoothing to reduce noise interference (prehistogram computation) has also been found beneficial in colour tonality discrimination [14, 150].

4 Colour Texture Analysis

Due to the increasing computational power and availability of colour cameras, there are rising demands to use colour when necessary. There has been a limited but increasing amount of work on colour texture analysis applied to surface inspection recently (cf. Table 1).

Most colour texture analysis techniques are borrowed from methods designed for graylevel images, such as co-occurrence matrices and LBP. This extension of graylevel texture analysis techniques to deal with colour images usually takes one of the following forms:

1. Processing each channel individually by directly applying graylevel based methods [16, 40, 41, 80, 71]: The channels are assumed independent to each other and only the spatial interactions are taken into account.

2. Decomposing image into luminance and chromatic channels [110, 105, 36, 91, 70]: Transforming the colour space so that texture features are extracted from the luminance channel and chromatic features from the chromatic channels, each in a specific manner. The selection of the colour space is usually application dependent.

3. Combining spatial interaction within each channel and interaction between spectral channels [115, 60, 104, 50, 125, 7, 88, 55, 45, 103]: The graylevel texture analysis techniques are applied in each channel, while the pixel interactions between different channels are also taken into account. Also, some works perform global colour clustering analysis, followed by spatial analysis in each individual stack.

Techniques independent of graylevel methods have also been attempted:

4. Using fully three dimensional models to analyse colour textures [53, 149]: The spatial and spectral interactions are simultaneously handled. The main difficulties arise in effectively representing, generalising, and discriminating three dimensional data.

Caelli and Reye [16] processed colour images in RGB channels using multiscale isotropic filtering. Features from each channel were then extracted and later combined for classification. In [40], the author used the KL transform to decorrelate the RGB channels into orthogonal eigenchannels. A recursive MRF model was performed in individual channels for texture segmentation. Later in [41], Haindl and Havlicek used a similar approach for colour texture synthesis. Mäenpää *et al.* [80] measured colour percentiles based on the accumulated histogram in each RGB channel as chromatic features, and co-occurrence matrices and LBP features as textural features to inspect wood surfaces. Lin [71] extracted wavelet features from each RGB channel separately to detect ripple-like defects in surface barrier layer chips.

Several works transform the RGB colour space to other colour spaces to perform texture analysis so that chromatic channels are separated from the luminance channel, e.g. [110, 105, 36, 91, 70]. In [105], Paschos *et al.* projected the colour images into the xyY colour space. The two chromaticity coordinates (x,y) were combined into one, which provided the chromatic features. Texture features were extracted from the Y channel. Dubuisson-Jolly and Gupta [36] used a multi-resolution simultaneous auto-regressive model to compute the texture features. Very simple colour features were selected from the Yuv colour space. Similarly, Monadjemi *et al.* [91] used hue-like colour features, and Hadamard and Gabor transform texture features to classify outdoor scenes. Liapis *et al.* [70] transformed colour images into the $L^*a^*b^*$ colour space in which discrete wavelet frame transform was performed in the L channel. Local histograms in a and b channels were used as chromatic features. Recently, Tsai *et al.* [130] also transformed colour images into the $L^*a^*b^*$ space, from which two chromatic representations were derived for each pixel colour, hue and chroma (colourfulness). Gabor filtering was then performed in these two channels. The authors argued that processing images in these two chromatic channels only could be resilient to illumination changes. They assumed that defects were chromatically differentiable. However, a large set of defects occur due to intensity irregularities. For example, changes in gray shade will not introduce differences in hue and chroma.

The importance of extracting correlation between the channels for colour texture analysis has been addressed by several authors. One of the earliest attempts was reported in [115]. In [104], Panjwani and Healey devised a MRF model to encode the spatial interaction within colour channels and between colour channels. A similar idea was explored in [55] for unsupervised colour image segmentation. In [50], Jain and Healey used Gabor filters to obtain texture features in each channel and opponent features that capture the spatial correlation between channels. Thai and Healey [125] applied multiscale opponent features computed from Gabor filter responses to model intra-channel and inter-channel interactions. In [88], Mirmehdi and Petrou perceptually smoothed the colour image textures in a multiresolution sense before segmentation. Core clusters were then obtained from the coarsest level and initial probabilities were assigned to all the pixels for all clusters. A probabilistic reassignment was then propagated through finer levels until full segmentation was achieved. Simultaneous auto-regressive models and co-occurrence matrices have also been used to extract the spatial relationship within and between RGB channels [7, 45, 103]. In [60], the authors performed colour clustering, followed by binarised spatial pixel distribution analysis, to identify textural defects in colour ceramic tile images. The colour clustering and binarisation in the spatial domain partially takes into account both spatial and spectral interactions.

There is relatively limited effort to develop fully 3D models to represent colour textures. The 3D data space is usually factorised using one of the approaches mentioned above, then the data is modelled and analysed using lower dimensional methods. However, such methods inevitably suffer from some loss of spectral information, as the colour image data space can only be approximately decorrelated. The epitome [53] and texem [149] models provide compact 3D representations of colour textures. The image is assumed to be a collection of primitives relying on raw pixel values in image patches. The neighbourhood of a central pixel in a patch are assumed statistically conditionally independent. In epitome, a hidden mapping guides the relationship between the epitome and the original image; in texem, specific mapping is provided by using multiple smaller epitomic representations. These compact representation methods inherently capture the spatial and spectral interactions simultaneously. However, full 3D methods are usually computationally expensive. Special hardware and software are necessary in order to adapt to real time performance.

Visual inspection using colour texture analysis is still largely under-developed in the literature and only a limited number of works have been reported so far. However, the demand for colour visual inspection is rising.

5 Classification and Novelty Detection

The primary goals of visual inspection are detection and classification. This involves choosing an appropriate decision making scheme which is usually referred to as pattern classification. Generally, this can be divided into supervised classification and unsupervised (or semi-supervised) classification. The following gives a brief review of these two approaches in relation to visual inspection.

5.1 Visual inspection via supervised classification

In supervised classification, the input pattern, based on features derived from earlier stages, is identified as a member of a pre-defined known class. This approach has been widely used in visual inspection, e.g. [144, 61, 122, 109, 90, 84, 74, 75].

The K-Nearest Neighbour (KNN) classifier is a simple nonparametric supervised distance-based learning algorithm where the pattern is assigned to the class shared by the majority of the K nearest neighbours. In [74, 75], Lopez *et al.* used KNN to classify ceramic tile surfaces based on chromatic features extracted from individual channels. The authors also investigated various values of K in terms of classification accuracy. Mandriota *et al.* [84] also applied KNN to classify filter responses and wavelet coefficients to inspect rail surfaces. Contrary to [74, 75], the authors did not find any performance improvement on their dataset by increasing the value K. Wiltsh *et al.* [144] used a parametric minimum distance based classifier to inspect steel images. Latif-Amet *et al.* [66] also used a Mahalanobis distance based parametric classifier. Recently, Pernkopf [109] classified steel surfaces based on data likelihood computed from coupled hidden Markov random fields. In [18], Chan and Pang classified four types of fabric defects by fitting into the expected feature model.

Artificial neural networks have been extensively used in decision making procedures due to their ability to learn complex non-linear input-output relationships. In [61], raw pixel values in textile images were extracted from local neighbourhood as the textural feature for each individual pixel. PCA was then applied to the feature vectors to reduce the feature space dimension. Finally, a feed-forward neural network was used to classify each pixel. Recently, Monadjemi *et al.* [90] applied a back propagation neural network and KNN to classify ceramic tile surfaces using various texture features, such as co-occurrence matrices, LBP, Gabor filtering, eigenfiltering, and discrete cosine transform. They proposed a neural network that generally outperformed the KNN classifier. Another popular network is the Self-Organising Map (SOM), which is mainly used for clustering and feature mapping [51]. Nisknen *et al.* [57, 96, 122] performed SOM based clustering of wood surfaces. However, although the clustering is unsupervised, the labelling of defect-free and defective samples in the SOM map was manually performed. Support vector machines (SVM) is also used to classify surfaces, such as [84] and [116]. For example, in [84], SVM was used to classify defects based features extracted from histograms, co-occurrence matrices, and shape information of defective regions.

Supervised classification have been demonstrated as a powerful approach when both training data and testing data are well-conditioned. For example, in [89], as high as 97.02% accuracy was achieved while using co-occurrence features and back propagation neural network, compared to 91.46% accuracy while using 7×7 eigen-filters and only trained on defect-free samples. However, supervised approach often involves a lengthy training stage and, more importantly, it requires a substantial number of defective samples, which for some applications can be difficult to obtain.

5.2 Visual inspection via novelty detection

In a novelty detection task, the classifier's task is to identify whether an input pattern is part of the data or it is in fact unknown. As for defect detection, it involves assigning a "normal" or "abnormal" label to a pattern (e.g. a surface or a pixel). Contrary to supervised classification, novelty detection only needs the normal samples for training purposes and usually uses a distance measure and a threshold for decision making. Recently, Markou and Singh [86, 87] gave a detailed review of novelty detection approaches, using statistical and neural network-based approaches.

Statistical parametric approaches are commonly used in visual inspection, for example [38, 132, 62, 9, 90]. The fundamental assumption is that the data distribution is Gaussian in nature. Thus, it can be easily statistically modelled based on means and covariances. As misclassifications can not be used as a criterion for the performance of a classifier as in a supervised manner, the available performance measure for novelty detection methods is the probability of false positives, that is rejection of good samples. Increasing the acceptance decision boundary will then obviously decrease the risk. However, it is also clear that the probability of false negatives depends on the acceptance region. Thus, it is usual to set the minimum acceptance region according to a fixed false positive probability. For example, in a parametric classifier, the decision boundary can be set as $\mu \pm k\sigma$ with $k = 2$ or $k = 3$, which corresponds to 5.0% and 0.3% expected false positive rate. In some applications, the decision boundary is simply set as the maximum range of normal samples in the training stage, e.g. [63, 64].

Probabilistic approaches, e.g. Gaussian mixture models, use kernel functions to estimate general distribution of training patterns. Each pattern is usually represented as a point in a d-dimensional feature space, where d is the length of the feature vector. The parameters of the model are determined by maximising the likelihood of the training data, usually through Expectation Maximisation (EM) algorithms. The objective is then to establish decision boundaries in the feature space and reject patterns that fall in regions of low density. The decision boundaries are determined by the probability distribution of the patterns at training stage. Thus, they can be conveniently computed by examining data likelihoods. In [149], two different mixture models are used to measure the pattern likelihoods. Novelty detection is then accomplished by using simple parametric thresholding, determined automatically from training data.

6 Conclusions

This review of recent advances in visual inspection using image processing techniques gives us some insights into the current state-of-the-art and possible trend of this application area. Although the research on visual inspection is diverse and ever-changing, the following observations can be made.

1. A significant amount of reported works are based on statistical and filter based approaches in visual inspection. This also could due to the fact that more texture analysis techniques fall in these categories than the others.

2. Filter bank based methods have been very popular in textural defect detection. The filters can be manipulated and designed in all sorts of directions and scales to decompose textures in order to highlight defects. However, it is notable that recent researches suggest contextual analysis which directly based on local neighbourhoods without dedicated filtering is a promising alternative approach.

3. Tonality defect detection, as a new emerging topic, should be viewed differently to textural defect detection. Its importance will be increasingly notable as more colour vision system will be used in practice.

4. There are significant and increasing amount of work on colour texture analysis, however, limited work has so far been reported in visual inspection using colour texture analysis The majority of the existing methods decompose the colour image into separate channels and process them independently or with limited interactions.

5. It is also notable that novelty detection is important in visual inspection where knowledge of defective patterns is usually incomplete and/or unavailable. However, when good prior knowledge is available, supervised classification scheme should be preferred as they often deliver better results.

6. In order to understand the formation and nature of the defects, it is important to be able to accurately localise the defective regions rather than classifying the surface as a whole. This can provide possibilities of classifying the defects and further studies of the characteristics of the defects. For example, in [65], Kunttu and Lepisto used Fourier shape descriptor to perform defect retrieval.

7. Real time performance is highly desirable for industrial application.

8. There is also a clear need of some standard datasets and well-defined experimental protocols in order to carry out fair comparative analysis.

References

[1] F. Ade. Characterization of texture by 'eigenfilter'. *Signal Processing*, 5(5):451–457, 1983.

[2] F. Ade, N. Lins, and M. Unser. Comparison of various filter sets for defect detection in textiles. In *International Conference on Pattern Recognition*, volume 1, pages 428–431, 1984.

[3] J. Ai, D. Liu, and X. Zhu. Combination of wavelet analysis and color applied to automatic color grading of ceramic tiles. In *International Conference on Pattern Recognition*, volume 3, pages 23–26, 2004.

[4] R. Baldrich, M. Vanrell, and J. Villanueva. Texture and color features for tile classification. In *SPIE Polarization and Color Techniques in Industrial Inspection*, volume 3826, pages 124–135, 1999.

[5] A. Baykut, A. Atalay, A. Ercil, and M. Güler. Real-time defect inspection of textured surfaces. *Real-Time Imaging*, 6:17–27, 2000.

[6] M. Bennamoun and A. Bodnarova. Digital image processing techniques for automatic textile quality control. *Systems Analysis Modelling Simulation*, 43(11):1581–1614, 2003.

[7] J. Bennett and A. Khotanzad. Multispectral random field models for synthesis and analysis of color images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(3):327–332, 1998.

[8] J. Besag. Spatial interaction and the statistical analysis of lattice systems. *Journal of Royal Statistical Society*, B-36:344–348, 1974.

[9] A. Bodnarova, M. Bennamoun, and S. Latham. Optimal Gabor filters for textile flaw detection. *Pattern Recognition*, 35:2973–2991, 2002.

[10] A. Bodnarova, J. Williams, M. Bennamoun, and K. Kubik. Optimal textural features for flaw detection in textile materials. In *Proceedings of IEEE TENCON'97 Conference*, pages 307–310, 1997.

[11] C. Boukouvalas, J. Kittler, R. Marik, and M. Petrou. Automatic grading of ceramic tiles using machine vision. In *IEEE International Symposium on Industrial Electronics*, pages 13–18, 1994.

[12] C. Boukouvalas, J. Kittler, R. Marik, and M. Petrou. Automatic color grading of ceramic tiles using machine vision. *IEEE Transactions on Industrial Electronics*, 44(1):132–135, 1997.

[13] C. Boukouvalas, J. Kittler, R. Marik, and M. Petrou. Color grading of randomly textured ceramic tiles using color histograms. *IEEE Transactions on Industry Electronics*, 46(1):219–226, 1999.

[14] C. Boukouvalas and M. Petrou. Perceptual correction for colour grading of random textures. *Machine Vision and Applications*, 12:129–136, 2000.

[15] R. Broadhurst, J. Stough, S. Pizer, and E. Chaney. Histogram statistics of local image regions for object segmentation. In *International Workshop on Deep Structure, Singularities, and Computer Vision*, 2005.

[16] T. Caelli and D. Reye. On the classification of image regions by colour, texture and shape. *Pattern Recognition*, 26(4):461–470, 1993.

[17] J. Campbell and F. Murtagh. Automatic visual inspection of woven textiles using a two-stage defect detector. *Optical Engineering*, 37:2536–2542, 1988.

[18] C. Chan and G. Pang. Fabric defect detection by Fourier analysis. *IEEE Transactions on Industry Applications*, 36(5):1267–1276, 2000.

[19] J. Chen and A. Jain. A structural approach to identify defects in textured images. In *IEEE International Conference on Systems, Man, and Cybernetics*, volume 1, pages 29–32, 1988.

[20] P. Chen, T. Liang, H. Yau, W. Sun, N. Wang, H. Lin, and R. Lien. Classifying textile faults with a back propagation neural network using power spectra. *Textile Research Journal*, 68:121–126, 1998.

[21] D. Chetverikov. Structural defects: General approach and application to textile inspection. In *Proceedings of the 15th International Conference on Pattern Recognition*, pages 1521–1524, 2000.

[22] R. Chin. Automated visual inspection: 1981 to 1987. *Computer Vision, Graphics, and Image Processing*, 41(3):346–381, 1987.

[23] C. Cho, B. Chung, and M. Park. Development of real-time vision-based fabric inspection system. *IEEE Transactions on Industrial Electronics*, 52(4):1073–1079, 2005.

[24] M. Clark and A. Bovik. Texture segmentation using Gabor modulation/demodulation. *Pattern Recognition Letters*, 6:261–267, 1987.

[25] J. Coggins and A. Jain. A spatial filtering approach to texture analysis. *Pattern Recognition Letters*, 3:195–203, 1985.

[26] F. Cohen, Z. Fan, and S. Attali. Automated inspection of textile fabrics using textural models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13(8):803–809, 1991.

[27] M. Comer and E. Delp. Segmentation of textured images using a multiresolution Gaussian autoregressive model. *IEEE Transactions on Image Processing*, 8(3):408–420, 1999.

[28] A. Conci and C. Proenca. A fractal image analysis system for fabric inspection based on box-counting method. *Computational Networks*, 30:1887–1895, 1998.

[29] A. Conci and C. Proenca. A system for real-time fabric inspection and industrial decision. In *14th International Conference on Software Engineering and Knowledge Engineering*, pages 707–714, 2002.

[30] R. Conners, C. McMillan, K. Lin, and R. Vasquez-Espinosa. Identifying and locating surface defects in wood: Part of an automated timber processing system. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 5:573–583, 1983.

[31] C. Coroyer, D. Declercq, and P. Duvaut. Texture classification using third order correlation tools. In *IEEE Signal Processing Workshop on High-Order Statistics*, pages 171–175, 1997.

[32] C. Costa and M. Petrou. Automatic registration of ceramic tiles for the purpose of fault detection. *Machine Vision and Applications*, 11:225–230, 2000.

[33] F. D'Astous and M. Jernigan. Texture discrimination based on detailed measures of the power spectrum. In *International Conference on Pattern Recognition*, pages 83–86, 1984.

[34] J. Daugman. Two-dimensional spectral analysis of cortical receptive field profiles. *Vision Research*, 20:847–856, 1980.

[35] R. De Valois, D. Albrecht, and L. Thorell. Spatial-frequency selectivity of cells in macaque visual cortex. *Vision Research*, 22:545–559, 1982.

[36] M. Dubuisson-Jolly and Gupta A. Color and texture fusion: Application to aerial image segmentation and GIS updating. *Image and Vision Computing*, 18:823–832, 2000.

[37] J. Escofet, S. Millan, H. Abril, and E. Torrecilla. Inspection of fabric resistance to abrasion by Fourier analysis. In *Proceedings of SPIE*, volume 3490, pages 207–210, 1998.

[38] J. Escofet, R. Navarro, M. Millán, and J. Pladellorens. Detection of local defects in textile webs using Gabor filters. *Optical Engineering*, 37(8):2297–2307, 1998.

[39] H. Habib, M. Yousaf, and M. Mohibullah. Modified laws energy descriptor for inspection of ceramic tiles. In *National Conference on Emerging Technologies*, pages 137–140, 2004.

[40] M. Haindl. Texture segmentation using recursive markov random field parameter estimation. In *Scandinavian Conference on Image Analysis*, volume 2, pages 771–776, 1999.

[41] M. Haindl and V. Havlicek. A simple multispectral multiresolution Markov texture model. In *International Workshop on Texture Analysis and Synthesis*, pages 63–66, 2002.

[42] J. Hammersley and P. Clifford. Markov field on finite graphs and lattices. unpublished, 1971.

[43] R. Haralick. Statistical and structural approaches to texture. *Proceedings of the IEEE*, 67(5):786–804, 1979.

[44] R. Haralick, K. Shanmugan, and I. Dinstein. Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, 3(6):610–621, 1973.

[45] O. Hernandez and A. Knotanzad. Color image segmentation using multispectral random field texture model & color content features. *Journal of Computer Science and Technology*, 4(3):141–146, 2004.

[46] Y. Huang and K. Chan. Texture decomposition by harmonics extraction from higher order statistics. *IEEE Transactions on Image Processing*, 13(1):1–14, 2004.

[47] J. Iivarinen. Surface defect detection with histogram-based texture features. In *SPIE Intelligent Robots and Computer Vision XIX: Algorithms, Techniques, and Active Vision*, volume 4197, pages 140–145, 2000.

[48] J. Iivarinen, J. Rauhamaa, and A. Visa. Unsupervised segmentation of surface defects. In *International Conference on Pattern Recognition*, volume 4, pages 356–360, 1996.

[49] A. Jain and F. Farrokhnia. Unsupervised texture segmentation using Gabor filters. *Pattern Recognition*, 24:1167–1186, 1991.

[50] A. Jain and G. Healey. A multiscale representation including opponent color features for texture recognition. *IEEE Transactions on Image Processing*, 7(1):124–128, 1998.

[51] A. Jain, P. Robert, and J. Mao. Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(1):4–37, 2000.

[52] W. Jasper, S. Garnier, and H. Potapalli. Texture characterization and defect detection using adaptive wavelets. *Optical Engineering*, 35:3140–3149, 1996.

[53] N. Jojic, B. Frey, and A. Kannan. Epitomic analysis of appearance and shape. In *IEEE International Conference on Computer Vision*, pages 34–42, 2003.

[54] I. Jolliffe. *Principal Component Analysis*. Springer-Verlag, 1986.

[55] Z. Kato, T. Pong, and S. Qiang. Unsupervised segmentation of color textured images using a multi-layer MRF model. In *IEEE International Conference on Image Processing*, pages 961–964, 2003.

[56] H. Kauppinen. A two stage defect recognition method for parquet slab grading. In *15th International Conference on Pattern Recognition*, volume 4, pages 803–806, 2000.

[57] H. Kauppinen, H. Rautio, and O. Silvén. Non-segmenting defect detection and SOM based classification for surface inspection using color vision. In *SPIE Conference on Polarization and Color Techniques in Industrial Inspection*, volume 3826, pages 270–280, 1999.

[58] C. Kim and A. Koivo. Hierarchical classification of surface defects on dusty wood boards. *Pattern Recognition Letters*, 15(7):713–721, 1994.

[59] S. Kim, M. Lee, and K. Woo. Wavelet analysis to defect detection in weaving processes. In *Proceedings of IEEE International Symposium on Industrial Electronics*, volume 3, pages 1406–1409, 1999.

[60] J. Kittler, R. Marik, M. Mirmehdi, M. Petrou, and J. Song. Detection of defects in colour texture surfaces. In *IAPR Machine Vision Applications*, pages 558–567, 1994.

[61] A. Kumar. Neural network based detection of local textile defects. *Pattern Recognition*, 36:1645–1659, 2003.

[62] A. Kumar and G. Pang. Fabric defect segmentation using multichannel blob detectors. *Optical Engineering*, 39(12):3176–3190, 2000.

[63] A. Kumar and G. Pang. Defect detection in textured materials using Gabor filters. *IEEE Transactions on Industry Applications*, 38(2):425–440, 2002.

[64] A. Kumar and G. Pang. Defect detection in textured materials using optimized filters. *IEEE Transactions on System, Man, and Cybernetics–Part B: Cybernetics*, 32(5):553–570, 2002.

[65] I. Kunttu and Lepistö. Shape-based retrieval of industrial surface defects using angular radius Fourier descriptor. *IET Image Processing*, 1(2):231–236, 2007.

[66] L. Latif-Amet, A. Ertuzun, and A. Ercil. An efficient method for texture defect detection: Subband domain co-occurrence matrices. *Image and Vision Computing*, 18(6-7):543–553, 2000.

[67] E. Levina. *Statistical Issues in Texture Analysis*. PhD thesis, University of California, Berkeley, 2002.

[68] S. Li. *Markov Random Filed Modeling in Image Analysis*. Springer, 2001.

[69] Y. Li and P. Gu. Free-form surface inspection techniques state of the art review. *Computer-Aided Design*, 36:1395–1417, 2004.

[70] S. Liapis, E. Sifakis, and G. Tziritas. Colour and texture segmentation using wavelet frame analysis, deterministic relaxation, and fast marching algorithms. *Journal of Visual Communication and Image Representation*, 15(1):1–26, 2004.

[71] H. Lin. Automated visual inspection of ripple defects using wavelet characteristics based multivariate statistical approach. *Image and Vision Computing*, 25:1785–1801, 2007.

[72] J. Liu and J. MacGregor. Estimation and monitoring of product aesthetics: Application to manufacturing of “engineered stone” countertops. *Machine Vision and Applications*, 16(6):374–383, 2006.

[73] F. Lopez, F. Acebron, J. Valiente, and E. Perez. A study of registration methods for ceramic tile inspection purposes. In *Proceedings of the IX Spanish Symposium on Pattern Recognition and Image Analysis*, volume 1, pages 145–150, 2001.

[74] F. Lopez, J. Valiente, R. Baldrich, and M. Vanrell. Fast surface grading using color statistics in the CIE Lab space. In *Iberian Conference on Pattern Recognition and Image Analysis (LNCS 3523)*, volume 2, pages 666–673, 2005.

[75] F. Lopez, J. Valiente, and J. Prats. Surface grading using soft colour-texture descriptors. In *Iberoamerican Congress on Pattern Recognition (LNCS 3773)*, pages 13–23, 2005.

[76] F. Lumbreras, R. Baldrich, M. Vanrell, J. Serrat, and J. Villanueva. Multiresolution texture classification of ceramic tiles. In S. Pandalai, editor, *Recent Research Developments in Optical Engineering*, pages 213–228. Signpost Research, 1999.

[77] F. Lumbreras, J. Serrat, R. Baldrich, M. Vanrell, and J. Villanueva. Color texture recognition through multiresolution features. In *International Conference on Quality Control by Artificial Vision*, volume 1, pages 114–121, 2001.

[78] T. Mäenpää and M. Pietikäinen. Texture analysis with local binary patterns. In C. Chen and P. Wang, editors, *Handbook of Pattern Recognition and Computer Vision*, pages 197–216. World Scientific, 3 edition, 2005.

[79] T. Mäenpää, M. Turtinen, and M. Pietikäinen. Real-time surface inspection by texture. *Real-Time Imaging*, 9(5):289–296, 2003.

[80] T. Mäenpää, J. Viertola, and M. Pietikäinen. Optimizing color and texture features for real-time visual inspection. *Pattern Analysis and Applications*, 6(3):169–175, 2003.

[81] J. Malik and P. Perona. Preattentive texture discrimination with early vision mechanisms. *Journal of the Optical Society of America, Series A*, 7:923–932, 1990.

[82] B. Mallick-Goswami and A. Datta. Detecting defects in fabric with laser-based morphological image processing. *Textile Research Journal*, 70:758–762, 2000.

[83] B. Mandelbrot. *The Fractal Geometry of Nature*. W.H. Freeman, 1983.

[84] C. Mandriota, M. Nitti, N. Ancona, E. Stella, and A. Distante. Filter-based feature selection for rail defect detection. *Machine Vision and Applications*, 15:179–185, 2004.

[85] J. Mao and A. Jain. Texture classification and segmentation using multiresolution simultaneous autoregressive models. *Pattern Recognition*, 25(2):173–188, 1992.

[86] M. Markou and S. Singh. Novelty detection: A review – part 1: Statistical approaches. *Signal Processing*, 83:2481–2497, 2003.

[87] M. Markou and S. Singh. Novelty detection: A review – part 2: Neural network based approaches. *Signal Processing*, 83:2499–2521, 2003.

[88] M. Mirmehdi and M. Petrou. Segmentation of color textures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(2):142–159, 2000.

[89] A. Monadjemi. *Towards Efficient Texture Classification and Abnormality Detection*. PhD thesis, University of Bristol, UK, 2004.

[90] A. Monadjemi, M. Mirmehdi, and B. Thomas. Restructured eigenfilter matching for novelty detection in random textures. In *British Machine Vision Conference*, pages 637–646, 2004.

[91] A. Monadjemi, B. Thomas, and M. Mirmehdi. Speed v. accuracy for high resolution colour texture classification. In *British Machine Vision Conference*, pages 143–152, 2002.

[92] C. Neubauer. Segmentation of defects in textile fabric. In *Proceedings of the 7th International Conference on Pattern Recognition*, volume 1, pages 688–691, 1992.

[93] T. Newman and A. Jain. A survey of automated visual inspection. *Computer Vision and Image Understanding*, 61(2):231–262, 1995.

[94] H. Ng. Automatic thresholding for defect detection. *Pattern Recognition Letters*, 27:1644–1649, 2007.

[95] M. Niskanen, H. Kauppinen, and O. Silvén. Real-time aspects of SOM-based visual surface inspection. In *Machine Vision Applications in Industrial Inspection*, pages 123–134, 2002.

[96] M. Niskanen, O. Silvén, and H. Kauppinen. Color and texture based wood inspection with non-supervised clustering. In *Proceedings of the 12th Scandinavian Conference on Image Analysis*, pages 336–342, 2001.

[97] P. Ohanian and R. Dubes. Performance evaluation for four classes of textural features. *Pattern Recognition*, 25(8):819–833, 1992.

[98] T. Ojala, M. Pietikäinen, and D. Harwood. A comparative study of texture measures with classification based on featured distribution. *Pattern Recognition*, 29(1):51–59, 1996.

[99] T. Ojala, M. Pietikäinen, and T. Mäenpää. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7):971–987, 2002.

[100] N. Otsu. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, Cybernetics*, 9(1):62–66, 1979.

[101] S. Özdemir, A. Baykut, R. Meylani, A. Ercil, and A. Ertüzün. Comparative evaluation of texture analysis algorithms for defect inspection of textile products. In *International Conference on Pattern Recognition*, pages 1738–1740, 1998.

[102] S. Özdemir and A. Ertüzün. Markov random field and Karhunen-Loève transforms for defect inspection of textile products. In *IEEE Conference on Emerging Technologies and Factory Automation*, volume 2, pages 697–703, 1996.

[103] C. Palm. Color texture classification by integrative co-occurrence matrices. *Pattern Recognition*, 37(5):965–976, 2004.

[104] D. Panjwani and G. Healey. Markov random field models for unsupervised segmentation of textured color images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(10):939–954, 1995.

[105] G. Paschos, P. Kimon, and P. Valavanis. A color texture based monitoring system for automated surveillance. *IEEE Transactions on Systems, Man, and Cybernetics - Part C*, 29(1):298–307, 1999.

[106] J. Penaranda, L. Briones, and J. Florez. Colour machine vision system for process control in ceramic industry. In *SPIE New Image Processing Techniques and Applications: Algorithms, Methods, and Components II*, volume 3101, pages 182–192, 1997.

[107] J. Penaranda, A. Pobil, and M. Serna. Classification system for pieces of Porcelanatto based on computer vision. In *SPIE Automated 3D and 2D Vision*, volume 2249, pages 339–348, 1994.

[108] F. Pernkopf. 3D surface inspection using coupled HMMs. In *Proceedings of the International Conference on Pattern Recognition*, pages 298–305, 2004.

[109] F. Pernkopf. Detection of surface defects on raw steel blocks using Bayesian network classifiers. *Pattern Analysis and Applications*, 7:333–342, 2004.

[110] R. Picard and T. Minka. Vision texture for annotation. *Multimedia System*, 3:3–14, 1995.

[111] M. Pietikainen, T. Maenpaa, and J. Viertola. Color texture classification with color histograms and local binary patterns. In *International Workshop on Texture Analysis and Synthesis*, pages 109–112, 2002.

[112] M. Ralló. Wavelet based techniques for textile inspection. In *Workshop on Wavelets and Applications*, pages 433–466, 2002.

[113] S. Ravandi and K. Toriumi. Fourier transform analysis of plain weave fabric appearance. *Textile Research Journal*, 65:676–683, 1995.

[114] T. Reed and J. Buf. A review of recent texture segmentation and feature extraction techniques. *Computer Vision, Image Processing and Graphics*, 57(3):359–372, 1993.

[115] A. Rosenfeld, C. Wang, and A. Wu. Multispectral texture. *IEEE Transactions on Systems, Man, and Cybernetics*, 12(1):79–84, 1982.

[116] I. Rossi, M. Bicego, and V. Murino. Statistical classification of raw textile defects. In *IEEE International Conference on Pattern Recognition*, volume 4, pages 311–314, 2004.

[117] H. Sari-Sarraf and J. Goddard. Vision systems for on-loom fabric inspection. *IEEE Transactions on Industry Applications*, 35:1252–1259, 1999.

[118] M. Schael. Texture defect detection using invariant textural features. In *DAGM Symposium*, pages 17–24, 2001.

[119] J. Scharcanski. Stochastic texture analysis for monitoring stochastic processes in industry. *Pattern Recognition Letters*, 26:1701–1709, 2005.

[120] K. Shiranita, T. Miyajima, and R. Takiyama. Determination of meat quality by texture analysis. *Pattern Recognition Letters*, 19:1319–1324, 1998.

[121] L. Siew, R. Hodgson, and E. Wood. Texture measures for carpet wear assessment. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 10:92–105, 1988.

[122] O. Silvén, M. Niskanen, and H. Kauppinen. Wood inspection with non-supervised clustering. *Machine Vision and Applications*, 13:275–285, 2003.

[123] K. Song, J. Kittler, and M. Petrou. Defect detection in random colour textures. *Image and Vision Computing*, 14:667–683, 1996.

[124] M. Swain and D. Ballard. Indexing via color histograms. *International Journal of Computer Vision*, 7(1):11–32, 1990.

[125] B. Thai and G. Healey. Modeling and classifying symmetries using a multiscale opponent color representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(11):1224–1235, 1998.

[126] F. Truchetet and O. Laligant. A review on industrial applications of wavelet and multiresolution based signal-image processing. *Journal Electronic Imaging*, 2008.

[127] D. Tsai and C. Heish. Automated surface inspection for directional textures. *Image and Vision Computing*, 18(1):49–62, 1999.

[128] D. Tsai and B. Hsiao. Automatic surface inspection using wavelet reconstruction. *Pattern Recognition*, 34:1285–1305, 2001.

[129] D. Tsai and T. Huang. Automated surface inspection for statistical textures. *Image and Vision Computing*, 21:307–323, 2003.

[130] D. Tsai, C. Lin, and K. Huang. Defect detection in coloured texture surfaces using Gabor filters. *Imaging Science Journal*, 53(1):27–37, 2005.

[131] D. Tsai and Y. Tsai. Defect detection in textured surfaces using color ring-projection correlation. *Machine Vision and Applications*, 13:194–200, 2003.

[132] D. Tsai and S. Wu. Automated surface inspection using Gabor filters. *The International Journal of Advanced Manufacturing Technology*, 16:474–482, 2000.

[133] I. Tsai, C. Lin, and J. Lin. Applying an artificial neural network to pattern recognition. *Textile Research Journal*, 65:123–130, 1995.

[134] M. Tuceryan and A. Jain. Texture analysis. In *Handbook of Pattern Recognition and Computer Vision*, chapter 2, pages 235–276. World Scientific, 1998.

[135] M. Turner. Texture discrimination by Gabor functions. *Biological Cybernetics*, 55:71–82, 1986.

[136] M. Unser. Texture classification and segmentation using wavelet frames. *IEEE Transactions on Image Processing*, 4(11):1549–1560, 1995.

[137] M. Unser and F. Ade. Feature extraction and decision procedure for automated inspection of textured materials. *Pattern Recognition Letters*, 2(3):185–191, 1984.

[138] L. Van Gool, P. Dewaele, and A. Oosterlinck. Texture analysis. *Computer Vision, Graphics and Image Processing*, 29:336–357, 1985.

[139] M. Varma and A. Zisserman. Texture classification: Are filter banks necessary? In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 691–698, 2003.

[140] F. Vilnrotter, R. Nevatia, and K. Price. Structural analysis of natural textures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8:76–89, 1986.

[141] H. Wechsler. Texture analysis - a survey. *Signal Processing*, 2:271–282, 1980.

[142] W. Wen and A. Xia. Verifying edges for visual inspection purposes. *Pattern Recognition Letters*, 20:315–328, 1999.

[143] R. Westra, J. Shippen, and N. Freear. Printing quality control using template independent neurofuzzy defect classification. In *Proceedings of the 7th European Conference on Intelligent Techniques and Soft Computing*, 1999.

[144] K. Wiltschi, A. Pinz, and T. Lindeberg. An automatic assessment scheme for steel quality inspection. *Machine Vision and Applications*, 12:113–128, 2000.

[145] E. Wood. Applying Fourier and associated transforms to pattern characterization in textiles. *Textile Research Journal*, 60:212–220, 1990.

[146] P. Xie and S. Guan. A golden-template self-generating method for patterned wafer inspection. *Machine Vision and Applications*, 11:225–230, 2000.

[147] X. Xie and M. Mirmehdi. Localising surface defects in random colour textures using multiscale texem analysis in image eigenchannels. In *Proceedings of the 12th IEEE International Conference on Image Processing*, volume 3, pages 1124–1127, 2005.

[148] X. Xie and M. Mirmehdi. Texture exemplars for defect detection on random textures. In *International Conference on Advances in Pattern Recognition*, pages 404–413, 2005.

[149] X. Xie and M. Mirmehdi. TEXEM: Texture exemplars for defect detection on random textured surfaces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(8):1454–1464, 2007.

[150] X. Xie, M. Mirmehdi, and B. Thomas. Colour tonality inspection using eigenspace features. *Machine Vision and Applications*, 16(6):364–373, 2006.

[151] B. Xu. Identifying fabric structure with fast Fourier transform techniques. *Textile Research Journal*, 66:496–506, 1996.

[152] X. Yang, G. Pang, and N. Yung. Fabric defect classification using wavelet frames and minimum classification error training. In *37th IAS Annual Meeting. Conference Record of the Industry Applications Conference*, volume 1, pages 13–18, 2002.

[153] X. Yang, G. Pang, and N. Yung. Robust fabric defect detection and classification using multiple adaptive wavelets. *IEE Proceedings Vision, Image Processing*, 152(6):715–723, 2005.

[154] H. Zhou, A. Kassim, and S. Ranganath. A fast algorithm for detecting die extrusion defects in IC packages. *Machine Vision and Applications*, 11:37–41, 1998.

[155] S. Zhu, Y. Wu, and D. Mumford. FRAME: Filters, random field and maximum entropy - towards a unified theory for texture modeling. *International Journal of Computer Vision*, 27(2):1–20, 1997.