Texture Analysis and Its Applications in Biomedical Imaging: A Survey

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(Methodological Review)

***Abstract*—Texture analysis describes a variety of image analysis techniques that quantify the variation in intensity and pattern. This paper provides an overview of several texture analysis approaches addressing the rationale supporting them, their advantages, drawbacks, and applications. This survey's emphasis is in collecting and categorising over five decades of active research on texture analysis. Brief descriptions of different approaches are presented along with application examples. From a broad range of texture analysis applications, this survey's final focus is on biomedical image analysis. An up-to-date list of biological tissues and organs in which disorders produce texture changes that may be used to spot disease onset and progression is provided. Finally, the role of texture analysis methods as biomarkers of disease is summarised.**

***Index Terms*—Biomedical imaging, computer-aided diagnosis, image analysis, texture analysis, texture biomarker, texture classification.**

I. Introduction

TEXTURE is one of the most significant characteristics of all types of images. Although image texture does not have an agreed-upon formal definition, it can be regarded as a function of pixel intensity or colour variation that form repeated patterns [1]. Computational studies on texture started with the work of Julesz [2] and, since then, texture has been studied in the context of classification, segmentation, synthesis, and shape.

Concerning the use of texture in classification, algorithms are designed to categorise a given textured image or region into one of a predefined set of texture classes. The use of texture includes image segmentation, in which images are split into regions of homogenous texture. Also, new images can be generated through texture synthesis. These are perceptually equivalent to a texture sample. Finally, texture also allows recovering the three-dimensional shape of a textured object present in an image. Classification, segmentation, and synthesis are closely related and widely studied, while shape from texture has received less attention.

The computation of features that describe texture is the core of texture analysis and can be performed by proposing mathematical definitions for image texture [3]. In several years of active research in this field, many kinds of theories and algorithms have emerged. However, the study of texture analysis can be traced back to 1962 when the theory of human visual perception of texture was studied, suggesting that texture might be modelled using k-th order statistics. Co-occurrence matrices were mainly driven by this perspective [4].

Human perception of texture has largely influenced the development of computer-based texture analysis methods. Experiments to understand how humans visually perceive texture established the "theory of textons" [2], which assumes that the preattentive discrimination of texture regions is based on textons' similarity and dissimilarity. Textons were first described as elementary texture elements such as blobs, corners, end-lines, and closures. In the early 1980s, the texton theory largely influenced the development of early classic texture analysis methods. Later, the texton concept was revisited, and texton was defined as a cluster centre in the filter response space [5]. This definition gave an operational power to the texton, enabling its automatic generation from images and launching the possibility of learning a universal texton dictionary for all images. Texton theory built a foundation for texture analysis and has inspired the development of a broad range of texture analysis approaches, ranging from structural to learning-based ones.

The research on texture analysis was mainly focused on spectral and model-based approaches in the late 1980s and early 1990s. Laws filter banks [6], Fourier transform [7], and

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wavelet transform [8] are examples of the spectral approach, while Markov random fields [9] and fractal models [10] are two major model-based approaches.

In the early 2000s, local binary patterns [11] appeared as promising local texture descriptors. Since then, several local binary patterns variants have been proposed [12]. Moreover, the need for invariant texture features led to the proliferation of local invariant methods such as the scale-invariant feature transform [13] and the histogram of oriented gradients [14].

The transition phase from handcrafted to learned approaches was started in 2001 with the bag-of-textons [5] (first), and the bag-of-words [15] approaches. A dictionary of words is created in these approaches, and images are presented as histograms over the dictionary. Since 2012, the research attention on deep-learning methods grew, and these have been applied in numerous problems in computer vision, including texture analysis [16]–[18].

Texture features have been used in many applications including, but not limited to, biomedical image analysis [19], quality inspection [20], content-based image retrieval [15], analysis of satellite or aerial imagery [21], face analysis [22], biometric identification [23], object recognition [24], and image compression [25].

Several reviews and surveys have been published over the years, providing insightful state-of-the-art checkpoints of the texture analysis field at different points in time. The majority of published surveys have reviewed and compared the classic approaches to texture analysis, namely the statistical, structural, spectral, and model-based methods [1], [26]–[29]. Over time, the reviews in texture analysis methods naturally adapted to the field's emerging trends. In [24], local-invariant texture descriptors were reviewed and compared. Recent surveys [30] and [12], focus on texture feature methods based on local binary patterns. One of the most recent reviews is focused on learning-based approaches [31]. Unsurprisingly, texture analysis reviews are influenced by the authors' field of application. Authors may choose to focus exclusively on one or two categories, leaving out the remaining ones if they are not relevant to their particular topic (e.g., biomedical applications [27] or document image retrieval [28]). In [27], a review centred on biomedical applications, the principles of some of the main texture analysis methods trending at the time were reviewed. Still, structural approaches were not covered in detail in reviews, given their limited applications in the field. Moreover, this field's heterogeneity, regarding its applications and the considered categorisation schemes, is reflected by how different authors review texture analysis methods.

This paper aims to provide a comprehensive and updated survey in texture analysis methods, covering all its classes, without an exclusive focus on any current trends or any particular applications. We provide a review of handcrafted and learned-based approaches in texture analysis. The classic handcrafted methods in texture analysis are addressed along with recently introduced categories. Both vocabulary-learned and deep-learning methods, which adapt convolutional neural networks for texture analysis, are addressed within the learned-based approaches. Furthermore, while texture analysis reviews typically address pure (isolated) texture analysis methods, we also address recently introduced integrative, or "hybrid," approaches, which combine the principles of multiple texture analysis methods. These integrative approaches have the advantage of achieving a good performance trade-off between different methods and have been gaining momentum.

This survey covers methods addressing static texture analysis only. Dynamic (temporal) is not addressed here. Also, all presented methods just address grey-level texture.

Finally, because of our work field, the second part of this review focuses on the application of texture analysis in the biomedical imaging field. The promising potential of texture analysis in oncology and neurology is reviewed, and the major challenges in biomedical texture analysis are discussed. An up-to-date list of the applications of texture analysis in biomedical imaging is presented in Section III.

II. Methods for Texture Analysis

This section provides a thorough review of texture feature computation methods. First, a granular categorisation of the methods is presented while addressing the classical approaches (II-A), the new categories in texture analysis (II-B), and the learning-based methods (II-C). Each class is briefly explained, and selected well-known representative methods are described. These methods are summarised in adjacent tables presenting their properties, application examples, and their performance in the corresponding application. Finally, the combinations of different texture analysis methods (integrative approaches) are covered in sub-Section II-D.

A. Classical Approaches

In texture analysis, existing methods are traditionally grouped into four categories: statistical, structural, spectral, and model-based approaches. These categories, commonly referred to as classical approaches, cover early texture analysis methods. An extensive review of these major classes in texture analysis is provided in sub-Sections II-A1 to II-A4.

A desirable texture feature is expected to capture the most representative texture information of a texture class, regardless of the variability in the imaging acquisition environments and settings, notably image rotation, scaling, and noise. To fulfil this, research in this field remains active and already led to several methods.

More recent texture analysis approaches use local descriptors based on binary patterns or local filters to compute local texture features. These approaches are the natural evolution of both statistical and spectral methods. Moreover, some local-invariant techniques are not explicitly designed for texture analysis, apart from their integration with vocabulary-learned processes (II-C).

Local descriptors can be divided into sparse and dense classes. A sparse descriptor first detects the input image's points of interest, followed by the sampling of a local patch and description of its invariant features. In contrast, a dense descriptor extracts local features for every pixel of the input image. Examples of those types are the scale-invariant feature transform (SIFT) and

LBP-based methods, respectively, for sparse and dense descriptors. These local approaches are addressed within sub-Section II-A1 and II-A3 and their corresponding tables.

1) Statistical Methods: Statistical methods are based on the analysis of the spatial distribution of grey-level values in the vicinity of an image's pixel. From this analysis, multiple statistics-based metrics can be computed. Depending on the number of pixels defining the local feature, statistical methods can be further categorised into first-order (one pixel), second-order (two pixels), and higher-order (three or more pixels) statistics.

First-order methods are frequently considered, even though only individual pixels' values matter, not their relations to neighbouring pixels. First-order statistical features (e.g., mean, maximum, minimum, variance, and kurtosis) are histogram-based descriptors of the grey-level distribution and can only provide global information on the targeted region. Histogram-based descriptors are computationally less costly and invariant to translation and rotation.

On the other hand, second-order statistical features describe interrelationships of grey-level intensities within a region. These features are computed from matrices that determine how often a pixel of intensity i finds itself within a particular spatial relation to another intensity j. For classification purposes, co-occurrence descriptors are, in general, more discriminative than histogram-based ones. Of these, the grey-level co-occurrence matrix (GLCM) and the grey-level run-length matrix (GLRLM) methods are the two most commonly used ones [32].

The GLCM considers the relationship between two pixels and computes the number of occurrences of all possible combinations of grey-level values in a particular direction and distance between these. While GLCMs are usually computed in eight directions, a common approach is to reduce these to four by combining opposite directions, resulting in a symmetric GLCM. The precise information on texture captured in the GLCM can be conveyed by several metrics, like those proposed by Haralick in [4].

The downsides of GLCMs are the high dimensionality of the matrices and the high correlation among the features. In practice, GLCMs are computed for several directions and distances, and only those presenting the best characteristics for the problem being addressed are kept. Nevertheless, the GLCM is one of the most well-known and thoroughly studied texture analysis methods, with an extensive list of applications. So far, it remains a benchmark approach for most comparative studies on texture classification.

Another approach is the GLRLM method, which evaluates sets of consecutive pixels, in a given direction, having the same grey-level value. These sets of consecutive pixels are called grey-level runs. The GLRLM provides numerical data from the lengths of the runs in a specific direction [33]. The GLRLMs are usually computed in four directions and a 2D (grey-level and length) run-length histogram is computed for each direction. A theoretical study [34] demonstrated that GLRLM features are not as useful as histogram-based and GLCM features for automatic texture classification.

Finally, higher-order statistical features that explore pixel relationships beyond pixel pairs are, in general, more robust to image noise [35].

Local binary patterns (LBP) [26] methods are categorised into the high-order statistical approaches class. They focus on the patterns of intensity transitions within the subregions of the region of interest. The LBP method combines the analysis of local structures, as in structural methods, with the analysis of occurrences, as in statistical methods. This combination renders good performance for texture analysis [11].

In the LBP method's original implementation [26], the local spatial structure is characterised by the sign of the difference between a pixel's intensity and its eight neighbouring pixels. An 8-bits binary vector is defined resulting from the direct comparison of each neighbour with the central pixel. This pixel is then labelled with the corresponding 8-bit binary code's decimal value, and the histogram of these LBP labels is used as a texture descriptor. LBP features can be computed by considering different radii to cover different spatial resolutions.

The LBP method's advantages are the ease of implementation, the low computational cost, and the invariance to monotonic illumination since it does not change the sign of the difference between two intensities. Despite these merits, the original LBP approach has significant drawbacks such as sensitivity to rotation and noise and capturing local texture only, thus failing to detect large-scale textural structures. Rotation-invariant LBP, uniform LBP, and rotation-invariant uniform LBP are three early modifications of original LBP addressing these limitations [11]. A recent LBP variant, the median robust extended LBP [36], is robust to image rotation and noise and was shown to have the best overall performance when evaluating robustness in multiple classification challenges [12].

Built upon the original LBP, several other LBP variants and extensions have been proposed, aiming to increase the robustness and improve the discriminative power while avoiding the original methods' drawbacks. For details on these variants and extensions, the reader is referred to recent reviews [12], [30], [37]. Notably, the LBP method has inspired several local-invariant methods, amongst which one can find the Weber local descriptor in [38] (see below) and the local phase quantisation in [39] (see Section II-A3).

Weber's local descriptor is based on Weber's law which states that the human perception of a pattern depends on both the change in a stimulus and that stimulus's initial intensity. This descriptor comprises two components, differential excitation and gradient orientation, quantified into 2D histograms, offering a global representation of texture. The Weber local descriptor depends on the local intensity variation and the magnitude of the central pixel's intensity. Using multiple neighbourhood sizes allows for the multi-scale generalisation of Weber descriptors. Furthermore, Weber descriptors are computationally efficient. Another method that uses the Weber law is the Weber LBP method [40], which effectively combines the Weber local descriptor's advantages with those of the LBP method.

The need for invariant texture features, to reduce or eliminate sensitivity to variable conditions like rotation, scale, orientation, and illumination, has expanded the development of

local-invariant methods. The scale-invariant feature transform (SIFT) and the histogram of oriented gradients (HOG) method are examples of those.

The histogram of oriented gradients (HOG) method [14] is an effective local descriptor, mainly used for object and face recognition. The underlying idea of HOG features is that local object appearances and shapes can be characterised by the distribution of the local intensity gradients or edge directions. The method involves counting the occurrence of gradient orientations; hence maintaining geometric and photometric transformation invariances. HOG has a strong texture and shape description ability and has been successfully applied to human detection [14], face recognition [41], and biomedical image analysis [42]–[44].

A SIFT descriptor is a 3D histogram of gradient locations and orientations. The interest points in SIFT are commonly detected with the difference of Gaussians, although other key-point detectors can be used [45]. The key-point dominant orientation is computed using a weighted histogram of quantised gradient orientations in local neighbourhoods. A vector descriptor is then formed by computing weighted histograms of relative orientations, concerning the dominant orientation in 4×4 blocks of pixels and eight orientations, resulting in a 128-dimensional descriptor. The principal component analysis SIFT (PCA-SIFT) method [46] is an extension of the SIFT descriptors with a reduced 36-dimensional feature vector. SIFT descriptors are scale-, rotation-, and affine-invariant. SIFT-based features have also been effectively combined with other texture analysis methods, namely a hybrid SIFT-LBP local-invariant method known as centre-symmetric LBP [47].

Most of the vocabulary-learned methods (that will be addressed later in II-C1) in texture analysis rely on SIFT descriptors as local texture descriptors. As far as in a recent review [48], learning-based approaches were grouped into SIFT-based and convolutional neural network-based (CNN-based) methods. Maximum response filters (MR filters) [49] and rotation-invariant feature transform (RIFT) method [50] are other examples of local-invariant methods with relevant contributions in texture analysis in the context of vocabulary-learned methods.

Other examples of statistical methods for texture analysis are the centre-symmetric auto-correlation [51], the variogram [52], the histogram of gradient magnitudes [53], the deterministic walk [54], and the computation of Tamura features [55].

Table I summarises the properties of some of these statistical approaches and provides examples of applications of those.

2) Structural Methods: Structural methods consider texture to be composed of several elements (called primitives) arranged according to regular or irregular placement rules. Identifying and locating the primitives representing different texture structures is the primary task in structural analysis, followed by their placement rules' inference.

Regions with uniform grey-level values, blobs, line segments, repetitive parallel edges, and fan-organised edges are considered examples of texture primitives. Such concepts for primitives make structural approaches particularly well-suited to the analysis of uniform and structured texture, but sub-optimal for the random type.

Mathematical morphology is a powerful tool for identifying texture primitives [124]–[126]. Morphological analysis is based on the concepts of "set theory". It tries to find objects and contours of different types or localise pixels' clusters with similar intensities through morphological operators. The mathematical morphology approach searches for spatial repetitiveness of existent shapes using structure elements (primitives). It has been successfully applied to texture analysis by granulometry.

Granulometry was first introduced to characterise size and shape information for binary images and was later extended to grey-scale image analysis [125]. In morphological granulometry, primitives are extracted by opening and closing morphological operators. The granulometric pattern spectrum corresponding to different primitives is computed, serving as placement rules for the morphology-based primitives. Properties of the granulometric pattern spectrum and its probability distribution function, such as the mean and standard deviation, can be used as texture features [126]. Granulometry reflects information regarding the shape and size of the structured texture pattern and the degree of granularity for unstructured texture patterns [127].

The Voronoi method [128] is another structure-based approach. It employs Voronoi tessellation to establish local relationships among texture primitives, allowing for the primitives' shapes to be obtained at a symbolic level. Following the Voronoi tessellation of an input image, different Voronoi polygons area moments are computed, reflecting the spatial distribution and shapes of the primitives, and serving as placement rules.

In [129], texture primitives were defined as the maximally connected set of pixels with the same pixel characteristics (e.g., intensity or gradient). Instead of inferring the placement rules from the spatial relationships between the primitives, other measures such as the intensity, orientation, elongation, and compactness of homogenous primitives are used in this structure-based method.

In [130], a structural analysis approach is proposed. Here the energy distribution in the Fourier power spectrum is used to infer the placement rules. Unlike the previously addressed structural methods, in this approach, the placement rules are assessed first. Then the primitives are extracted using those placement rules combined with phase information. This method can also be considered a structural-spectral hybrid approach.

Structural approaches provide a beneficial symbolic description of an image [27]. According to the concept of primitives and placement rules, structural approaches are based on regularity, hence more appropriate for analysing pattern texture.

The properties of some of the structural methods and examples of applications are summarised in Table II.

3) Spectral Methods: The visual system's cells perform a frequency and orientation analysis that have motivated the development of spectral methods [138]. These methods, also known as filter-based or transform-based methods, are used for the multi-scale and multiresolution representation of texture. Spectral methods can analyse the frequency content of texture strictly in the spatial domain (e.g., Laws filters [6]), strictly in the frequency domain (e.g., Fourier transform [7]), or both, frequency and spatial domains (e.g., Gabor [139] and wavelet transform [8]).

TABLE I
STATISTICAL METHODS IN TEXTURE ANALYSIS

Methods	Properties[†]	Applications	Reported Performance (%)[††]
Binarised statistical image features [56]	• Local descriptor + Rotation-invariant + Statistically meaningful texture representation	• Face recognition [56] • Image quality assessment [57] • Osteoporosis diagnosis [58]	• Acc: 50–70 • *n/a* • Acc: 63–77
Centre-symmetric auto-correlation [51]	+ Rotation-invariant	• Computer-aided diagnosis in Barrett's oesophagus [59]	• Acc: 6–76, Sen: 50–87, Spe: 52–82
Centre-symmetric local mapped pattern [60]	• Local descriptor + Invariant to partial viewpoint changes + Scale-, illumination-, and rotation-invariant	• Human epithelial type 2 cell classification [61]	• Sen: 87–90
Deterministic walk [54]	+ Images simultaneously explored in all scales	• Plant leaf texture classification [62] • Identification of wear particles [63]	• Acc: 95–98 • *n/a*
First-order statistics methods [4]	+ Translation- and rotation-invariant + Easy to compute	• Biomedical image analysis [64]–[66]	• Acc: 70–100[‡]
Grey-level co-occurrence matrix (GLCM) [4]	+ Broad scope of applications – High matrix dimensionality – Highly correlated features	• Defect detection [67]–[69] • Text detection [70] • Identification of oil spills in synthetic-aperture radar (SAR) images [71] • Biomedical image analysis [65], [72]–[82]	• *n/a* • *n/a* • *n/a* • Acc: 70–100[‡], AUC: 55–95[‡], Sen: 50–100[‡], Spe: 47–98[‡]
Grey-level run-length matrix (GLRLM) [33]	• Adequate for textures containing several dominant scales	• Automated recognition of drill core textures [83] • Biomedical image analysis [64], [65], [79], [84]–[88]	• Acc: 57–100[‡] • Acc: 70–100[‡], Sen: 81–97[‡], Spe: 61–98[‡]
Grey-level entropy matrix (GLEM) [89]	• Robustness depends on window size + Rotation-invariant	• Oncologic image analysis [89]–[91]	• Acc: 61–70
Histogram of gradient magnitudes [53]	+ Rotation-invariant + Low computational complexity	• Classification satellite-imagery dataset [53]	• Acc: 51–79
Histogram of oriented gradients (HOG) [14]	• Local descriptor + Geometric and photometric transformation invariant	• Face recognition [41] • Biomedical image analysis [42]–[44], [92], [93]	• Acc: 55–95 • Acc: 6–100[‡], AUC: 88–90, Sen: 76–84, Spe: 88–92
Local binary patterns (LBP) [26]	+ Low computational cost + Invariant to monotonic illumination changes + Noise- and rotation-sensitive	• Real-time surface inspection [94] • Defect detection on ceramic surface [95] • Defect detection on wood surfaces [96] • Hybrid fingertip matching [97] • Face recognition [98] • Biomedical image analysis [19], [92], [99]–[104]	• Acc: 87–99 • *n/a* • *n/a* • *n/a* • Acc: 64–97 • Acc: 12–100[‡], AUC: 69–99, Sen: 56–75, Spe: 62–100
Local directional pattern [105]	• Local descriptor + Robust to noise and illumination variations	• Breast cancer classification [100] • COVID-19 detection [106] • Face recognition [105]	• Acc: 74–76, AUC: 84–90 • Acc: 47–54 • Acc: 69–97
Local energy pattern [107]	• Local descriptor + Preserves local structure information + Relatively invariant to imaging conditions	• Material categorisation [107]	• Acc: 59–97
Local jet pattern [108]	• Local descriptor + Scale-, reflection-, and rotation-invariant	• Texture classification [108]	• Acc: 98–99
Local ternary pattern [109]	• Local descriptor + Robust to noise + Rotation-invariant	• Brain MR image analysis [110] • Texture classification [111]	• Acc: 75–93 • Acc: 54–99
Patch intensity[a] [112]	• Local descriptors + Rotation-invariant – Computationally expensive	• Texture classification [112]	• Acc: 94–97
Scale-invariant feature transform (SIFT)[a] [13]	• Local descriptor + Scale- and viewpoint-invariant	• Classifying celiac disease [113] • Diagnosis of malaria [114] • Matching medical images [115]	• AUC: 78 • Acc: 84–94 • *n/a*
Speed up robust features (SURF)[a] [116]	• Local descriptor + Rotation-invariant + Scale-invariant	• Face recognition [117]	• Acc: 95–97
Rotation-invariant feature transform (RIFT)[a] [50]	• Local descriptor + Affine-invariant + Invariant to viewpoint changes and non-rigid deformations – Memory and computation-intensive	• Sparse texture representation [50]	• Acc: 77–95
Tamura features [55]	• Derived from psychophysical models + Correspond to human visual perception	• Historical document image analysis [118] • Texture analysis in linguistic terms [119]	• Acc: 16–90 • *n/a*
Variogram [52]	+ Simple + Easy to interpret in graph form	• Classification of SAR images of urban areas [120] • Forest airborne image classification [121] • Mass detection in mammograms [122]	• Acc: 43–52[‡] • Acc: 77–86[‡] • Acc: 70–96, Spe: 67–95
Weber local descriptor [38]	• Local descriptor + Robust to noise	• Face recognition [40] • Gender recognition from face images [123]	• Acc: 87–98 • Acc: 88–99

[a] These local-invariant methods are mainly ported to texture analysis in the context of vocabulary-learned methods (see II-C1).
[†] Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
[††] Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; AUC: area under the receiver operating characteristics (ROC) curve; Sen: sensitivity; Spe: specificity. n/a: not applicable.
[‡] In combination with other texture features.

TABLE II
STRUCTURAL METHODS IN TEXTURE ANALYSIS

Methods	Properties†	Applications	Reported Performance (%)††
Morphological granulometry [125]	+ Scale-invariant	• Defect detection in fabrics [131] • Defect detection in printed circuit boards [132] • Inspection and segmentation of leather fabric [133] • Texture classification in OCT data [134]	• Acc: 97 • Acc: 94–100 • *n/a* • Acc: 53–63
Shape index histograms [135]	• Based on second-order image structure • Well suited for blob-like structures	• Classification of HEp-2 cell [135]	• Acc: 71–80
Topographic map [136]	• Encode geometric information + Illumination-invariant	• Satellite image indexing [137]	• Acc: 32–95
Voronoi method [128]	• Identify interior and border regions of the texture	• Texture segmentation [128] • Classification of pap smears [87]	• *n/a* • *n/a*

† Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
†† Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy. n/a: not applicable.

Applying simple filters, like Laws filters and steerable filters, was a pioneering approach in early spectral-based implementations. In filtering approaches, the frequency information is computed by convolving the image with filters, resulting in a filter response set. Texture features are usually based on the statistics of those filter responses. Laws [6], developed a set of filters by mutual products of so-called Laws texture energy measures: level, edge, spot, wave, and ripple. The responses to Laws filters represent meaningful texture patterns. On the downside, these are not rotationally invariant.

A fundamental approach to frequency domain analysis is the one performed by applying the Fourier transform. A 2D Fourier transform decomposes an image into its frequency components and represents it as a weighted combination of vertical and horizontal sinusoids of various frequencies. Fourier texture features contain frequency information of the texture but cannot describe local texture variations. A windowed Fourier transform [140], in which the frequency information is computed within a window, was proposed for computing Fourier texture features to overcome the above limitation, thus, providing information at the local level. A particular case of the windowed Fourier transform is the Stockwell transform, where the window function is Gaussian. The Stockwell transform has been applied in biomedical texture analysis [141]–[143]. Fourier texture features are translation-invariant and capable of handling noise.

The local frequency descriptors method [144] and the local phase quantisation method [39], both based on the windowed Fourier transform, compute texture features with local frequency descriptors robust to noise and blur.

The local phase quantisation method is based on computing the Fourier transform phase for a local window, consecutively centred in every image's pixel. First, the local frequency is computed using a short-term Fourier transform on a local neighbourhood at each image's pixel. Then, four low-frequency components are considered, and the phase information of these is recorded by observing the signs of their real and imaginary parts, resulting in an 8-bit binary code. Each pixel is then labelled with the corresponding decimal value, and the histogram of these labels are used in the spirit of LBP as local phase texture features. This phase information of the low-frequency components is shown to be ideally invariant to centrally symmetric blur, thus yielding descriptors tolerant to the most common types of image blurs. Furthermore, since only phase information is used, the method is also invariant to non-uniform illumination. The local phase quantisation methods have been effectively combined with the LBP methods, presenting enhanced texture features for face recognition [145].

In a distinct approach, Gabor filters are very effective in texture representation and discrimination. A Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. A multichannel filtering approach is performed through a bank of Gabor filters at different scales and orientations. A Gabor filter bank performs a robust multiresolution decomposition that allows the computation of frequency and orientation information. Gabor texture features are computed from the statistical distribution of the Gabor magnitude responses. Gabor features are robust against photometric disturbances, such as illumination changes and noise. At the same time, they fail to reach the expected level of performance in the presence of rotation, scale, and affine variations. The combination of Gabor filters with LBP has resulted in texture features with reasonable robustness [146].

Wavelet transform, on the other hand, analyses texture in the spatial and frequency domains. A wavelet-based approach approximates an image by dilations and translations of a given basis function, known as mother wavelet. The discrete wavelet transform can be computed using a pyramid structure implemented with a pair of low-pass and high-pass filters, followed by down-sampling. The obtained wavelet coefficients and the measures computed from them (such as energy, variance, and entropy, among others) are commonly used as wavelet texture features. The wavelet transform has the advantage of providing variations of the spatial resolution, therefore representing texture at the most suitable scale.

Furthermore, the flexibility in the choice of the wavelet function is an advantage for specific applications. While the wavelet transform is not invariant to rotations, attempts towards rotation-invariant texture analysis can be found, as in [147]. Combining the dual-tree complex wavelet transform and the LBP method has resulted in rotation-, illumination-, and scale-invariant texture features [148].

TABLE III
SPECTRAL METHODS IN TEXTURE ANALYSIS

Methods	Properties[†]	Applications	Reported Performance (%)[††]
Fourier transform [7]	• Encodes frequency domain information + Translation-invariant	• Fabric defect detection [149], [150] • Video text detection [151] • Biomedical image analysis [75], [77], [152]	• *n/a* • Acc: 81–99 • Acc: 74–90[‡], Sen: 50–100[‡], Spe: 47–95[‡]
Gabor filters [139]	+ Encode both spatial and frequency domain information + Robust multiresolution decomposition + Robust to illumination changes	• Defect detection [153], [154] • Quality inspection of steel [155] • Ceramic materials characterisation [156] • Text detection [157] • Fingerprint texture analysis [158] • Biomedical image analysis [159]–[162]	• *n/a* • Acc: 65–79 • Acc: 30–74 • Pre: 49–64, Rec: 42–76 • *n/a* • Acc: 81–97, AUC: 40–100, Sen: 75–100, Spe: 72–100
Laws filters [6]	+ Identify meaningful texture patterns − Not rotationally invariant	• Biomedical image analysis [75], [84], [163]–[166]	• Acc: 30–90[‡], Sen: 50–100[‡], Spe: 47–98[‡]
Leung-Malik (LM) filters[a] [5]	• Local descriptor + Scale- and rotation-invariant	• Natural material characterisation [5] • Texture classification [49]	• Acc: 87 • Acc: 75–98
Local frequency descriptor [144]	• Local descriptor + Robust to noise + Rotation-invariant	• Texture classification [144]	• Acc: 89–99
Local phase quantisation [39]	• Local descriptor + Invariant to uniform illumination changes + Robust to blurring	• Blurred texture classification [39] • Face recognition [145]	• Acc: 88–93 • Acc: 81–95
Locally encoded transform feature histogram (LETRIST) [167]	• Local descriptor + Robust to Gaussian noise + Robust to viewpoint changes + Rotation-, illumination-, and scale-invariant	• Bioimage classification [168] • Texture classification [167] • COVID-19 identification [169]	• Acc: 90–93 • Acc: 97–100 • Acc: 87–98[‡]
MR filters[a] [49]	• Local descriptor • Low-dimensional filter response space + Rotation-invariant	• Texture classification [49] • Brain tumour classification [170] • Lung nodule classification [171]	• Acc: 71–98 • Acc: 62[‡] • Acc: 60[‡]
Riesz transform [172]	+ Translation-invariant + Rotation-invariant	• Lung texture classification [173] • 3D solid texture classification [174]	• Acc: 78 • Acc: 12–100
Shearlet transform [21]	+ Robust to noise + Rotation-invariant	• Face recognition [175] • Texture classification and retrieval [176]	• Acc: 14–82 • Acc: 79–99
Schmid filters[a] [177]	• Local descriptor • Gabor-like filters + Rotation-invariant	• Texture classification [49]	• Acc: 76–98
Steerable pyramid [178]	• Orientation-selective filters + Covers multiple scales and different orientations	• Texture classification [179] • Thyroid nudle classification in ultrasound images [180]	• Acc: 93–97 • Acc: 92–99
Stockwell transform [181]	• Preserves the phase information + Encodes both spatial and frequency domain information + Rotation-invariant	• Texture characterisation [182] • Biomedical image analysis [141]–[143]	• Acc: 83–95 • AUC: 94, Sen: 93, Spe: 96
Wavelet transform [8]	+ Encode both spatial and frequency domain information + Represents texture at different scales	• Defect detection [183]–[185] • Monitoring industrial processes and quality of manufactured products [186], [187] • Agriculture and food quality inspection [188] • Text detection [189], [190] • Sea ice detection in SAR images [191] • Biomedical image analysis [64], [82], [134], [192]	• Acc: 96–98 • Acc: 77 • *n/a* • Acc: 42–94, Rec: 86–92 • *n/a* • Acc: 57–100[‡]

[a] These methods are mainly ported to texture analysis in the context of vocabulary-learned methods (see II-C1).
[†] Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
[††] Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; AUC: area under the receiver operating characteristics (ROC) curve; Pre: precision; Rec: recall; Sen: sensitivity; Spe: specificity. n/a: not applicable.
[‡] In combination with other texture features.

A list of different spectral methods with their properties and examples of applications are summarised in Table III.

4) Model-Based Methods: In model-based approaches, the fundamental qualities of texture are captured by a model chosen from a set of models that range from complex network-based, random field, and fractal-based ones to Wold decomposition models, whose estimated parameters of the selected model indeed represent particular texture properties. The critical issue in model-based methods is the correct model's choice and how to map a specific texture into it effectively. For most model-based methods, the texture is modelled probabilistically (Markov random field model), geometrically (fractal model), or as a set of basis functions (Wold decomposition).

Probabilistic models include random field models such as the Markov random field (MRF) approach, which models textures as a stochastic process, characterising them as distributions of random variables. An MRF model assumes that a pixel's intensity depends only on the previous pixel intensity in a chain

TABLE IV
MODEL-BASED METHODS IN TEXTURE ANALYSIS

Methods	Properties[†]	Applications	Reported Performance (%)[††]
Auto-regressive models [203]	• A spatial pixel interaction model + Simplicity in parameter estimation + Suitable for coarse textures	• Defect detection in web inspection systems [204] • Unsupervised texture segmentation [205] • Biomedical image analysis [64], [66], [82], [206]	• *n/a* • *n/a* • Acc: 70–100[‡]
Complex network models [207]	+ Relatively rotation-invariant – Not robust to noise – Difficulty in estimating a large number of model parameters	• Pattern recognition [208] • Classification of froth flotation production states [209]	• Acc: 37–98 • Acc: 75–95
Fractal models [10]	• Shape description + Low computational cost – Feature stability is resolution-dependent	• Defect detection in fabric [210], [211] • Defect detection in steel surfaces [212] • Biomedical image analysis [213]–[220]	• Acc: 76–96 • Acc: 98–99 • Acc: 60–94[‡], AUC: 75–93
Markov random field models (MRF) [9]	• Probabilistic model + Rotation-variant	• Real-time defect inspection [221] • Model defect-free textile web [222] • Biomedical image analysis [223]–[225]	• Acc: 92–97 • *n/a* • Acc: 86[‡], Pre: 50–100[‡]
Wold decomposition [201]	• Measure the randomness, direction, and periodicity of the texture	• Unsupervised texture segmentation [226]	• *n/a*

[†] Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
[††] Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy. n/a: not applicable.
[‡] In combination with other texture features.

and on a transition probability matrix [193]. In other words, the MRF model builds an undirected graph with neighbour pixels as random variables. The parameters of the model are estimated with an optimisation method that aims to minimise an energy function. The optimised parameters of the MRF model define the texture and can be used as texture features. Texture features based on MRF models are generally rotation-variant, as is the case of the anisotropic circular Gaussian MRF [194] that computes rotation-invariant texture features.

Fractal models [10] make use of mathematical tools for dealing with scale in texture analysis. These are appropriate for images where texture consists of patterns with a certain degree of self-similarity across scales. Here, the fractal dimension [195], which computes the change of details in a fractal pattern with the scale, offers a global description of geometric objects' complexity and irregularity. Fractal sets may share the same fractal dimensions while having different appearances. For this reason, lacunarity has been proposed as a complementary measure for the fractal dimension [196]. Lacunarity can distinguish between different texture appearances, if presenting the same fractal dimension, by measuring a fractal's deviation from being translationally invariant.

In [197], the fractal-based models are revisited, and the multifractal spectrum method invariant to viewpoint changes, nonrigid deformations, and local affine illumination changes is proposed.

The combination of the multifractal spectrum method with other texture analysis methods, such as the wavelet transform [198], the LBP method [199], and the scale-invariant feature transform [200], has resulted in more discriminative texture features. The fractal features' stability depends on the image's resolution, which is a common drawback of all fractal-based models.

The Wold decomposition method [201] models texture by decomposing it into three mutually orthogonal components that measure the texture's periodicity, randomness, and direction. The flexibility in choosing the parameters of these three components provides a wide range of texture modelling. However, the difficulty in estimating the coefficients and selecting the correct model is a downside of this approach. A 3D texture model based on Wold decomposition is proposed in [202].

The complexity in estimating several model parameters, which usually increases with the considered window size, makes model-based approaches less prevalent than statistical and spectral techniques.

Model-based methods and their applications are summarised in Table IV.

B. New Categories in Texture Analysis

As techniques from other areas are incorporated into image texture research, the need to define new categories arises. The classic categorisation of texture analysis methods has been extended from four classical classes to seven categories in [227], including the graph-based and the entropy-based approaches addressed here.

1) Graph-Based Methods: A graph is a collection of vertices (nodes) and the connections (edges) between them. In graph-based methods, texture features are extracted from the corresponding graph defined over an image. The local graph structures method [228], the graph of tourist walk approach [229], and the shortest paths in graphs approach [230] are the methods in this category of texture analysis.

In the local graph structures method, texture features are computed from the local graph neighbourhood. The local graph consists of six vertices, including the target pixel, and eight edges connecting them. The target pixel's value is chosen as the initial threshold. Moving anti-clockwise (clockwise) along the edges of the left (right) vertices, starting in the targeted pixel and back, a binary code is produced: 1 if moving to a higher or equal pixel's value, 0 if moving to a lower pixel's value. The target pixel is labelled with the decimal value of the

TABLE V
GRAPH-BASED METHODS IN TEXTURE ANALYSIS

Methods	Properties†	Applications	Reported Performance (%)††
Graph of tourist walks [229]	– Complex computation	• Flotation froth texture extraction [233]	• Acc: 87–92
Local graph structures [228]	• Contain information on local micro-pattern + Fast computation + Invariant to shift and scale	• Clothing classification [234] • Face recognition [228] • Texture classification [231]	• Acc: 82–91 • Acc: 94–99 • Acc: 71–75
Shortest paths in graphs [230]	+ Encode both macro and micro-texture information	• Biomedical image analysis [235]	• AUC: 77–90

† Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
†† Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; AUC: area under the receiver operating characteristics (ROC) curve.

8-bit binary number that results from the edge labels, and the histogram of these local graph labels are used as texture features. Based on this method, another one, called extended local graph structure method, was proposed [231]. It captures further spatial information by visiting neighbour pixels, both clockwise and anti-clockwise. Local graph structure contains discriminative local information and is computationally efficient.

The graph of the tourist walks method is based on deterministic tourist walks and graph theory. In this method [62], a traveller explores an image according to a given memory and walking rule, resulting in partially self-avoiding trajectories. These trajectories can be used to build a graph that describes the tourist transitivity and, as a result, the texture pattern. The measures computed from this graph (graph degree and joint degree) are used as texture descriptors. This approach has been effectively extended to dynamic texture analysis in [232].

Shortest paths in graphs is another graph-based method that has been proposed for texture analysis. In this method, the image's pixels are regarded as vertices of an undirected weighted graph, whose weights are defined by the image's grey-level values. The shortest paths are computed in the set of four vertices (pixels) of graphs that correspond to diagonal points of square regions of the texture. The shortest paths can be computed in different nonoverlapping square regions while reducing their size, in a multi-scale approach, starting from the original texture size. Hence, the texture features that are computed from shortest-paths contain both micro and macro texture information.

The properties and examples of the application of graph-based methods are summarised in Table V.

2) Entropy-Based Methods: The category of entropy-based approaches was introduced as a new category in texture analysis in [227]. Entropy-based methods are based on the extensions of entropy measures from the information-theory field. Even though these methods look promising, they need additional time and research attention to become well-established and gain momentum in texture analysis.

In the field of signal processing, entropy-based measures evaluate the irregularity of signals. Sample entropy is one of the most well-known entropy measures, quantifying the unpredictability of subsequent samples of data-series based on the previous samples' knowledge. In [236], the sample entropy was extended to two dimensions to measure irregularity in pixel patterns. In 2D approaches, the unpredictability associated with entropy is computed in a window, taking into account the spatial distribution of the intensities within that window, compared to sample windows of the same size. Accordingly, 2D sample entropy [237], 2D distributed entropy [238], and 2D multi-scale entropy [239] methods have been proposed for texture analysis. In [237], discriminative and rotation-invariant texture features are computed using 2D sample entropy measures. However, the process is computationally expensive. Hence, 2D distributed entropy and 2D multi-scale entropy measures have been proposed to overcome this drawback. In general, these 2D entropy-based methods perform well for irregular and intricate textures and are easy to implement. Sample entropy has also been extended to multidimensional and fuzzy sample entropy for colour texture classification [240].

Table VI summarises the properties of entropy-based methods and presents application examples of those.

C. Learning-Based Approaches

Learning-based methods are dataset-dependent approaches that were first developed in the context of texture recognition via the bag-of-textons method [5]. In this method, a dictionary of textons is generated by learning textons from different texture classes, and each texture is represented as a histogram of textons. This approach was generalised in the bag-of-words method (BoW), in the context of image retrieval [15], and later for image classification [45]. The methods within this framework are referred to as the vocabulary-learned methods. Learning-based approaches have been extended to deep-learning methods by applying CNN models for texture analysis. In this survey, learning-based approaches are categorised as vocabulary-learned and deep-learning methods.

1) Vocabulary-Learned Methods: Vocabulary-learned methods, when applied to texture analysis, are adapted to learn a dictionary that contains texture elements computed by local descriptors. These methods represent texture based on an orderless aggregation of local features.

Typically, vocabulary-learned methods take the following approach: extraction of local descriptors, clustering to learn the dictionary, feature encoding, and pooling into a global descriptor. The local descriptors in these methods can be sparse or dense local descriptors. The most common local descriptors in

TABLE VI
ENTROPY-BASED METHODS IN TEXTURE ANALYSIS

Methods	Properties†	Applications	Reported Performance (%)††
2D distributed entropy [238]	+ Rotation-invariant	• Irregularity analysis of small-sized texture [238]	• *n/a*
2D multi-scale entropy [239]	+ Effective classification, depending on the texture pattern	• Pseudoxanthoma elasticum (PXE) detection [241] • Texture classification [239]	• *n/a* • Pre: 54–62, Rec: 51–63
2D sample entropy [237]	+ Rotation-invariant + Translation-invariant − Computationally expensive	• Age discrimination of rat sural nerves [237] • Classification of lymphomas [236] • Colorectal cancer classification [240]	• AUC: 84 • AUC: 69–100 • AUC: 98

† Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
†† Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. AUC: area under the receiver operating characteristics (ROC) curve; Pre: precision; Rec: recall. n/a: not applicable.

TABLE VII
VOCABULARY-LEARNED METHODS IN TEXTURE ANALYSIS

Methods	Properties†	Applications	Reported Performance (%)††
Bag-of-words (BoW) [5], [45]	+ Higher flexibility compared to handcrafted features − Require a large dictionary	• Brain tumour classification [170] • Histopathological image classification [245] • Natural material characterisation [5]	• Acc: 59–62, AUC: 59–63 • Acc: 70–97 • Acc: 87
Fisher vector (FV) [242]	• Encode higher-order statistics + Require a small dictionary	• Texture classification [246]	• Acc: 63–99
Improved Fisher vector (IFV) [243]	+ Pre-eminent performance in texture classification + Require a small dictionary	• Texture classification [17]	• Acc: 58–99
Vector of locally aggregated descriptors (VLAD) [244]	+ A simplified version of FV + Require a small dictionary	• Texture classification [17]	• Acc: 53–99

† Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
†† Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; AUC: area under the receiver operating characteristics (ROC) curve.

the vocabulary-learned framework include LM filters [5], MR filters [49], SIFT [13], RIFT [50], patch intensity [112], and LBPs [11].

Feature encoding is the core component of vocabulary-learned methods. In this step, the local descriptors' information is encoded in a single vector, either using voting techniques, as in the BoW method or by extracting high-order statistics, as in the Fisher vector (FV) method [242].

The most intuitive encoder was introduced in [5] and generalised to a baseline BoW method, which yields a histogram representation of local descriptors by counting the number of local features assigned to each codeword.

In the FV method, the high-order statistics are extracted by encoding additional information from the local descriptors' distribution. Based on the FV method, improved Fisher vector (IFV) [243] and vector of locally aggregated descriptors (VLAD) [244] methods were proposed. The IFV method has achieved the best performance in texture classification according to comprehensive comparisons between FV, IFV, and VLAD methods in [17].

Even though vocabulary-learned methods were not developed initially for texture analysis, they provide powerful texture feature computation tools.

Table VII summarises the properties of vocabulary-learned methods and their examples of applications.

2) Deep-Learning Methods: The most promising image classification result was recorded for a deep convolutional neural network known as AlexNet [16] in 2012. Since then, deep-learning approaches have also been applied to texture analysis, and several convolution neural network-based texture representation methods have been proposed.

A CNN consists of multiple trainable building blocks accumulated on top of one another. A wide range of CNN models have been developed, including AlexNet [16], VGGNet [247], GoogleNet [248], ResNet [249], and DenseNet [250], with a continuously growing depth. CNN models are trained on large-scale datasets, among which the most commonly used one is ImageNet, with 1000 classes and 1.2 million images [251].

Recent work on CNNs has illustrated that, with minor modifications, pre-trained CNNs on large datasets can perform well for texture analysis [18], [252]. In [18], the CNN features were computed from a convolutional layer's output and combined with traditional encoders towards global representation. Based on this approach, the FV-CNN method was proposed in [253], has achieved impressive results on texture recognition in clutter datasets. In this method, a CNN pre-trained on ImageNet is used as a feature extractor, and an orderless representation is built using FV.

The power of CNNs in computing deep-learned texture features has not been not fully exploited. According to [252],

TABLE VIII
DEEP-LEARNING METHODS IN TEXTURE ANALYSIS

Methods	Properties[†]	Applications	Reported Performance (%)[††]
B-CNN [255]	+ Good representation ability − Very high dimensional features	• Texture classification [256]	• Acc: 70–81
Deep-TEN [258]	+ Dictionary-learning + More flexible framework (allow arbitrary input image size) + Superior performance in transferring pre-trained CNN features	• Liver lesion detection [260]	• Acc: 59–70
FASON [261]	+ Combining information from the multiple levels of convolutional layers + Effectively trainable in an end-to-end manner	• Texture recognition [261]	• Acc: 72–93
FV-CNN [253]	• Using pre-trained CNN models (AlexNet on ImageNet) + Better texture classification performance than AlexNet	• Object and scene recognition [18] • Material recognition [18]	• Acc: 68–81 • Acc: 63–68
NetVLAD [257]	+ Directly trainable in an end-to-end manner	• Place recognition [257]	• Rec: 64–80
T-CNN [254]	• Combining output from multiple convolutional layers + Lower complexity compared to classic CNNs	• Dynamic texture classification [262] • Tissue image classification [263]	• Acc: 65–100 • Acc: 25–100

[†] Properties are listed as descriptions (•), advantages (+) and disadvantages (-) of the methods.
[††] Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; Rec: recall.

fine-tuning CNN models is expected to be predominant over pre-trained CNN models on task-specific datasets. In a fine-tuned CNN, the global image representation is usually generated end-to-end; that is, the network will render the final visual representation without additional explicit encoding or pooling steps.

A texture CNN (T-CNN) was developed in [254], which includes an energy layer to extract the dense response to intermediate features in the network. The network was trained end-to-end and improved the results on texture classification tasks while reducing the complexity compared to classic CNNs.

A bilinear CNN model (B-CNN) was developed in [255]. It combines two networks to extract and classify translation-invariant local pairwise features in a CNN framework and allows end-to-end training for both networks. The B-CNN method is beneficial for fine-grained categorisation. It has also been applied to texture classification, with slightly better performance than FV-CNN [256].

A fusion network for texture recognition known as FASON [256] was proposed integrating the ideas of the T-CNN method and the complete BCNN method. FASON combines first and second-order information flow and enables more content and style learning by end-to-end training than B-CNN.

The CNNs and orderless pooling methods, such as VALD and FV, were integrated in an end-to-end manner in the NetVLAD [257] and deep texture encoding network (Deep-TEN) [258]. In NetVLAD, a VLAD-like layer was plugged into a CNN network at the last convolutional layer and enabled end-to-end training. NetVALD was initially designed for place recognition and later applied to texture classification [167], though with lower classification performance than FV-CNN. In Deep-TEN, an encoding layer integrated at the top of convolutional layers has combined orderless pooling encoding such as VLAD and FV in a CNN trained end-to-end. The orderless encoding integrated into the Deep-TEN method makes it particularly appropriate for material and texture recognition.

Deep-learning models can automatically learn high-level features from raw data, although their performance depends on the number of training samples. Also, the size of the dataset used for pre-training and fine-tuning significantly influences the fine-tuning performance. In [254], it was shown that fine-tuning a pre-trained network on a texture-centric dataset obtains better results on another texture dataset than a network pre-trained on an object-centric dataset. The primary constraint of applying neural networks in texture analysis is the need for actual training data.

In [37], several texture descriptors were evaluated and compared with several LBP variants. It was found that CNNs outperform the LBP variants despite their much higher computational complexity. While CNNs usually outperform classical texture descriptors, their effectiveness in resource-limited settings is yet to be determined. In [259], a CNN-LBP hybrid approach was proposed to address this issue.

Table VIII summarises the properties of deep-learning methods and their examples of applications.

D. Integrative Approaches

Several approaches in texture analysis integrate different methods aiming to highlight additional texture information. The so-called hybrid methods commonly include combinations of benchmark approaches with other methods, porting two or even more approaches into a single framework to compute enhanced texture features. These combinations can join methods of the same class, such as the statistical hybrid approaches ([264]–[267]); methods from two different classes, such as the statistical-spectral hybrid approaches ([145], [146], [148], [268]); or even bridge the gap between classic techniques and

CNN architectures, to form handcrafted deep convolutional networks such as the ScatNet [269] and PCANet [270].

The co-occurrence of uniform LBP method [265], the pairwise rotation-invariant co-occurrence LBP method (PRICoLBP) [264], and the co-occurrence histograms of oriented gradients method [267] are examples of statistical hybrid approaches. These methods follow similar frameworks that exploit spatial co-occurrence encoding to boost LBP and HOG methods' discriminative power and robustness. The spatial co-occurrence of features in these methods can provide higher-order statistical information than their individual occurrence. The enhanced PRICoLBP features capture the spatial context co-occurrence information effectively and are rotation-invariant. The PRICoLBP features have been applied effectively for visual classification after incorporating the multi-scale and multi-orientation colour information [264].

Based on the concept of lacunarity in fractal analysis, a hybrid fractal-LBP approach was proposed in [199]. In this integrative method, the lacunarity analysis has been performed on multi-scale LBPs to characterise the spatial distribution of texture structure, yielding highly discriminative texture features (in comparison to some LBP variants [167]) with strong robustness to photometric and geometric changes.

In [200], the multifractal analysis is integrated with SIFT, a well-established local descriptor, in a tight wavelet frame system. This method has inherited the fractal dimension's high-discriminative power, the invariance to most environmental changes of the SIFT method, and the multi-scale representation of the wavelet frame system.

The integration between methods has not been limited to handcrafted approaches, and classic-deep hybrid convolutional networks have also been proposed. Following the standard CNN architecture, a scattering convolutional network (ScatNet) was proposed in [269]. The convolutional filters in ScatNet are simply Gabor or Haar wavelets, and no learning is required. ScatNet computes translation-invariant texture features that preserve high-frequency information. In [271], ScatNet was extended to compute scale-, deformation-, and rotation-invariant texture features.

Another hybrid convolutional network (PCANet), based on trained principal component analysis (PCA) filters and LBP encoding, was proposed in [270]. The feature extraction in PCANet is much faster than ScatNet, but with weaker invariance properties and lower texture classification performance. Moreover, Deep-TEN [258] and NetVLAD [257] (discussed earlier in sub-Section II-C2) are two CNNs that can be referred to as inter-class hybrid networks (vocabulary-learned-deep-learning hybrid networks).

A list of hybrid methods with their combinations and properties are summarised in Table IX.

III. Texture Analysis in Biomedical Imaging

Biomedical imaging is one of the most widespread areas for the application of texture analysis. Texture analysis has been applied in a variety of biomedical applications, including medical image enhancement [279], [280], automatic and semi-automatic segmentation [159], [281], and detection and monitoring of different diseases [282]–[284]. The first reported use of texture analysis within the biomedical field was in radiographic imaging and dates back to 1971 [285]. Since then, the application of texture analysis in several medical imaging modalities grew continuously.

The common limitation of all imaging modalities is that image interpretation is based on the human visual system's input. Potential features within each image may not be perceived easily by the naked eye and pass unnoticed. Texture features can play a complementary role in biomedical image analysis. It was shown that statistical and spectral texture features can outperform the visual assessment of magnetic resonance imaging [282].

On the other hand, while texture analysis can take part in the estimation of fracture risk in osteoporosis (outperforms the estimation with bone mineral density evaluation [58]) and for assessment of the healing process after bone loss [286], when representing the micro-architectural alteration of bone in digital X-rays, it is not of real use for the diagnosis of, e.g., bone fracture.

The robustness of texture analysis cooperates in the monitoring of disease progression and therapy assessment. Computer-aided diagnosis (CAD) tools have been developed to complement the detection, analysis, and monitoring of several diseases [59], [93], [287], [288] by using texture features. In this section, the potential of texture analysis in two promising application areas is discussed, namely oncology and neurology imaging. In Table X, the application of different texture analysis methods in various disorders is summarised. Finally, the concept of 3D texture and its relevance in biomedical imaging are addressed in sub-Section III-C.

A. Oncologic Imaging

In oncologic practice, different imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron emission tomography (PET) are used both separately or in combination, depending on the tumour type and location. In oncology, the role of imaging is to help answer clinical questions such as the confirmation of diagnosis, characterisation of lesions, staging, treatment planning, targeting therapy, assessing treatment response, and surveillance [284]. Texture features can assist in answering all these questions.

Oncologic applications of texture analysis fall into cancer prognosis, diagnosis, and treatment response evaluation. Tumours are heterogeneous both on genetic and histopathological levels. Tumour spatial heterogeneity is an important prognostic factor and can be quantified by texture. In [336], the association of tumour heterogeneity, as assessed by CT image texture analysis, with tumour metabolism, stage, and survival in oesophageal cancer was studied. The use of first-order statistics-based features (computed from autocovariance matrix) of CT images in liver lesions, to classify them as benign or malignant, has shown promising [310]. Fractal-based texture features were employed to classify small lung lesions in high-resolution CT images

TABLE IX
HYBRID METHODS IN TEXTURE ANALYSIS

Group (category)	Methods	Combination	Properties
Classical (model-based + spectral)	Anisotropic circular Gaussian MRF [194]	• Fourier transform & MRF	• Rotation-invariant
	Linear regression model based on wavelet transform [272]	• Linear regression model & Wavelet	• Consider the correlation between frequency regions
	Multi-resolution MRF [273]	• MRF & Wavelet	• Contained the high-pass and low-pass components of wavelet decomposition in a model
	Multi-scale fractal [200]	• Fractal & SIFT & Wavelet	• Robust to illumination change and local geometric change
	Wavelet multifractal spectrum [198]	• Fractal & Wavelet	• Robust to scale and rotation changes
	Wavelet-based multifractal spectrum [274]	• Fractal & Wavelet	• Easy implementation • Robust to environmental changes
Classical (model-based + statistical)	Local configuration pattern [275]	• LPB & Microscopic configuration modelling	• Robust to illumination variations • Rotation-invariant
	Pattern lacunarity spectrum [199]	• Lacunarity & LBP	• Robust to photometric and geometric changes
Classical (spectral + spectral)	Steerable pyramid based Laws' masks [179]	• Laws filters & Steerable pyramid	• Texture features at different levels and different orientations
Classical (statistical + spectral)	Dominant LBP [276]	• Gabor & LBP	• Less sensitive to noise • Robust to image rotation
	LBP dual-tree complex wavelet transform [148]	• LBP & Wavelet	• Rotation-, illumination-, and scale-invariant
	LBP histogram Fourier [268]	• Fourier transform & LBP	• Rotation-invariant
	LBP local phase quantisation [145]	• LBP & Local phase quantisation	• Discriminative spatial-frequency features
	Local Gabor binary pattern histogram sequence [146]	• Gabor & LBP	• Illumination-invariant
Classical (statistical + statistical)	Center-symmetric LBP[47]	• LBP & SIFT	• Computationally inexpensive • Relatively short feature histogram • Robust to illumination changes
	Co-occurrence histograms of oriented gradients [267]	• Co-occurrence & HOG	• Effective for object classification
	Co-occurrence of uniform LBP [265]	• Co-occurrence & LBP	• Capture spatial context co-occurrence effectively
	HOG-gist [b] [277]	• gist & HOG	• Texture description ability is stronger than traditional gist
	HOG-LBP [266]	• HOG & LBP	• Handling partial occlusion
	LBP Weber local descriptor [40]	• LBP & Weber local descriptor	• Robust to lighting • Robust to noise
	Pairwise rotation-invariant co-occurrence LBP [264]	• Co-occurrence & LBP	• Capture spatial context co-occurrence effectively • Rotation-invariant
Classical (spectral) + Learning-based (deep-learning)	ScatNet [269]	• CNN & Gabor wavelets	• Features being stable to deformation • Preserving high-frequency information
Classical (statistical) + Learning-based (deep-learning)	Local binary CNN [259]	• CNN & LBP	• Reduce the computational complexity of CNNs • Well suited for learning and inference of CNNs in resource-constrained environments
	PCANet [270]	• CNN & LBP	• Weak invariance properties

[b] See [278] for more details on computing "gist" features.

[174]. In [304], CNN-based features have been used to automatically extract features from shear-wave elastography (SWE) data to classify the malignant and benign breast tumours. Texture features have also been applied in lesion classification and detection in MRI images of the brain (e.g., Gabor features [160]), breast (e.g., 3D GLCM features [303]), liver (e.g., GLCM, GLRLM, auto-regressive, and wavelet features [66]), cervix (e.g., first- and second-order statistics and deep-learned features [306]) and prostate (e.g., fractal and multifractal features [215]), suggesting a promising role for texture analysis in oncology.

Texture features can assess tumour characteristics before treatment. In various primary and metastatic tumours, texture features associated with histopathologic characteristics may be useful in treatment planning and prognostication. In [337], primary colorectal tumours were evaluated using volumetric texture assessment. It was found that different contrast-enhanced CT image texture features, such as entropy, uniformity, kurtosis, skewness, and standard deviation of the histogram, were predictive of survival, regardless of the tumour stage. In another study [324], patients with oesophageal cancer treated

TABLE X
LIST OF ORGANS/TISSUES WHERE TEXTURE ANALYSIS METHODS HAVE BEEN APPLIED, INDICATING THE PATHOLOGY AFFECTING THE TISSUE AND THE IMAGING MODALITY USED. IN THE "OBJECTIVE" (OBJ) COLUMN, C REPRESENTS CLASSIFICATION APPLICATIONS, WHEREAS S REPRESENTS SEGMENTATION APPLICATIONS

Organ	Disease	Imaging technique	Texture feature	Obj	Reported Performance (%)†
Bladder	Bladder cancer	CT	First-order statistics, GLCM, and Fourier features [77]	C	*n/a*
		OCT	First-order statistics, GLCM, Laws, and Fourier features [75]	C	Sen: 50–100, Spe: 47–88
Bone	Osteoporosis	X-ray	GLCM, GLRLM, and binarised statistical image features [58]	C	Acc: 50–87
		X-ray	HOG and Gabor features [43]	C	Acc: 80–93
		X-ray	Laws features [163]	C	*n/a*
Brain	Acute ischemic stroke	CT and MRI	GLCM features [289]	C	AUC: 50–84
		MRI	GLCM features [81]	C	*n/a*
	Alzheimer's disease	MRI	3D features (GLCM, GLRLM, and gradient) [65]	C	Acc: 63–98
		MRI	3D wavelet features [290]	C	AUC: 57–97, Sen: 72–89, Spe: 65–94
		MRI	First-order statistics, GLRLM, Laws, and fractal features [164]	C	Acc: 83–98
		MRI	GLCM features [74]	C	*n/a*
		MRI	Voxel-based GLCM features [291]	C	Acc: 89–100
		OCT	GLCM features [292]	C	*n/a*
		PET	Trace transform triple features [293]	C	Acc: 70–94
		SPECT	3D first-order statistical features [294]	C	Acc: 92
	Amyotrophic lateral sclerosis	MRI	GLCM features [78]	C	AUC: 85, Sen: 83, Spe: 79
	Brain tumours	Digital microscopy	Bag-of-word (based on MR8 filters) [170]	C	Acc: 59–80, AUC: 59–83
		Digital microscopy	Riesz wavelet and deep-learned features [295]	C	Acc: 62–99, Sen: 86–99, Spe: 87–100
		MRI	First-order statistics and GLCM features [72]	C	Acc: 74–100
		MRI	First-order statistics, Gabor, and fractal features [296]	C–S	Pre: 83–89, Sen: 82–88
		MRI	First-order statistics, GLCM, and GLRLM features [86])	C–S	AUC: 73–98, Sen: 55–100, Spe: 66–100
		MRI	Fractal and fractal wavelet features [297]	C–S	Acc: 88–96
		MRI	Histogram and GLCM features [298]	C	*n/a*
		MRI	Gabor features [160]	C	Acc: 81–91, AUC: 77–92
		MRI	Stockwell transform features [141]	C	Sen: 93, Spe: 96
		MRI and CT	Fractal features [220]	S	*n/a*
	Epilepsy	MRI	3D GLCM and GLRLM features [85]	C	*n/a*
		MRI	GLCM features [80]	C–S	Sen: 61–85, Spe: 100
		MRI	Wavelet, multi-wavelet and wavelet packet features [192]	C	Acc: 50–100
	Machado-Joseph disease	MRI	GLCM features [76]	C	AUC: 50–100
	Multiple sclerosis	MRI	3D deep-learned features [299]	S	Acc: 52–78
		MRI	GLCM features [300]	C	Acc: 60–100
		MRI	GLCM, GLRLM, auto-regressive, and wavelet features [64]	C	Acc: 58–100
		MRI	Polar Stockwell transform features [143]	C	*n/a*
	Parkinson's disease	MRI	First-order statistics, GLCM, and GLRLM features [79]	C	AUC: 95, Sen: 76–91, Spe: 66–75
		MRI	GLCM [301]	C	*n/a*
		SPECT	First-order statistics and GLCM features [302]	C	*n/a*
Breast	Breast cancer	DCE-MRI	Volumetric (3D) GLCM features [303]	C	*n/a*
		Digital mammograms	Variogram and cross-variogram features [122]	C–S	Acc: 70, Sen: 100, Spe: 67
		Dynamic contrast-enhanced MRI (DCE-MRI)	GLCM features [73]	C	AUC: 70
		Mammography	LBP, Elliptic LBP, and local directional pattern features [100]	C	Acc: 67–77, AUC: 78–92
		MRI	GLCM, GLRLM, auto-regressive model, and wavelet features [82]	C	Acc: 80–100
		Optical coherence microscopy (OCM)	LBP, average LBP, and block-based LBP features [99]	C	Acc: 67–100
		Ultrasonography	GLCM and GLRM features [288]	C	Acc: 90, Sen: 84, Spe: 96
		Ultrasound	First-order statistics, GLCM, and fractal features [219]	C–S	Acc: 88, Sen: 83, Spe: 92
		SWE	Deep-learned features [304]	C	Acc: 92–95, Sen: 87–96, Spe: 93–95
Cervix	Cervical cancer	Digital microscopy	Gabor features [161]	C	Acc: 89, Sen: 84–89, Spe: 85
		Digital microscopy	GLCM, fractal, GLRLM, and Voronoi diagram features [87]	C	AUC: 59–95
		MRI	First-order statistics and GLCM features [305]	C	Acc: 53–100, Sen: 63–100, Spe: 0–100
		MRI	First- and second-order statistics and deep-learned feature [306]	C	Acc: 46–76, Sen: 43–95, Spe: 22–77
		MRI	Deep-learned features [307]	C	Acc: 60–82, AUC: 66–88, Sen: 42–88, Spe: 62–83

† Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; AUC: area under the receiver operating characteristics (ROC) curve; Pre: precision; Sen: sensitivity; Spe: specificity. n/a: not applicable.

Colon	Colorectal cancer	Contrast-enhanced CT	Fractal features [217]	S	*n/a*
		Digital microscopy	2D and fuzzy sample entropy [240]	C	AUC: 98, Sen: 81, Spe: 100
		MRI	First-order statistics features [308]	C	AUC: 59–90, Sen: 66–100, Spe: 44–88
Liver	Chronic liver disease	Contrast-enhanced CT	GLCM, GLRM, histogram-based and Laws features [84]	C	AUC: 50–74
	Fatty liver disease	MRI	GLCM, GLRLM, auto-regressive model, and wavelet transform [66]	C	Acc: 65–100
		Ultrasound	First-order statistics, GLCM, and Laws features [165]	C	Acc: 95
		Ultrasound	Gist feature [309]	C	Acc: 69–98, Sen: 88–100, Spe: 62–100
	Hepatic tumours	CT	Auto-covariance features [310]	C	Acc: 81, Sen: 75, Spe: 88
Lung	COVID-19	CT	First-order statistics, GLCM, and GLRLM features [311]	C	AUC: 86–100
		CT	GLCM features [312]	C	Acc: 96
		X-ray	Deep-learned features [313]–[315]	C	Acc: 84–100, AUC: 92–99
		X-ray	GLCM features [316]	C	Acc: 98, Sen: 96, Pre: 100
		X-ray	LBP features [317]	C	Acc: 94, Sen: 95, Spe: 93
		X-ray and CT	GLCM, GLRLM, local directional pattern, and discrete wavelet features [106]	C	Acc: 47–99, Sen: 31–99, Spe: 51–99
		X-ray and CT	GLCM, LBP, and deep-learned features [318]	C	Acc: 79–100, AUC: 59–100
		X-ray	LBP, LPQ, LETRIST, and deep-learned features [169]	C	Acc: 87–98
	Lung cancer	Contrast-enhanced CT	Fractal features [216]	C	*n/a*
		CT	2D and 3D LBP features [101]	C	Acc: 36–78
		CT	GLCM and deep-learned features [319]	C	Acc: 84–97, Sen: 85–98, Spe: 75–96
		CT	LBP and HOG features [44]	C	Acc: 90–98, Sen: 62–91, Spe: 92–99
		CT	SIFT, HOG, MR8 and LBP features [171]	C	Acc: 45–90
		CT and PET	Laplacian of Gaussian and first-order statistics [320]	C	Acc: 78
	Obstructive lung diseases	CT	First-order statistics, GLCM and GLRLM features [321]	C	Acc: 55–83, Sen: 21–91, Spe: 69–97
		CT	LBP features [102]	C	Acc: 61–95
	Tuberculosis	X-ray	Gist and HOG features [93]	C	Acc: 86–94
		X-ray	GLCM features [322]	C–S	*n/a*
	Pneumonia	CT	3D Riesz wavelet features [323]	C	*n/a*
		X-ray	Deep-learned features (AlexNet) [319]	C	Acc: 82–97, Sen: 86–97, Spe: 75–96
Oesophagus	Barrett's oesophagus	Digital microscopy	Fractal, MRF, and GLRLM features [223]	C–S	*n/a*
		Endoscopic OCT	Center-symmetric auto-correlation features [59]	C	Acc: 70–84, Sen: 69–82, Spe: 71–74
	Oesophageal cancer	CT	First-order statistics features [324]	–	*n/a*
		PET	Fractal features [325]	C	*n/a*
Ovarian	Ovarian cancer	Microscopy	GLEM features [90]	C	Acc: 62–70, Sen: 41–60, Spe: 73–75
		OCT	GLCM and Fourier features [326]	C	Acc: 67–78
Prostate	Prostate cancer	Light microscopy	GLEM and GLRLM features [89]	C	Acc: 65–85
		Microscopy	Fractal, GLCM, Gabor, and multi-wavelet features [214]	C	Acc: 60–94
		MRI	Fractal and multifractal features [215]	C–S	AUC: 75–93
		Ultrasound	Gabor features [159]	S	*n/a*
Retina	Glaucoma	Fundus photography	GLCM and MRF features [224]	C	Acc: 86
		OCT	GLCM and GLRLM features [327]	C	Acc: 83–90
		OCT	GLCM, GLRLM, LBP, wavelet, and granulometry features [134]	C	Acc: 53–85
		OCT	Wavelet features [328]	C	Acc: 95, Sen: 93, Spe: 96
	Macular pathologies	OCT	LBP and HOG features [92]	C	Acc: 56–100
		OCT	LBP features [103], [104]	C	Acc: 68–81, AUC: 93
		OCT	Linear configuration pattern features [329]	C	Acc: 89–98
Skin	PXE	Dermoscopy	2D multi-scale fuzzy entropy features [241]	C	*n/a*
	Skin cancer	Dermoscopy	GLCM features [330]	C	Acc: 76–100
		OCT	First-order statistics, fractal and MRF features [225]	C	Pre: 50–100
Thyroid	Thyroid cancer	MRI	GLCM, auto-regressive, and wavelet features [206]	C	Acc: 89
		Ultrasound	Steerable pyramids and GLCM features [180]	C	Acc: 92–99
Uterus	Uterine sarcomas	MRI	First-order statistics, GLCM, and Gabor features [331]	C	Acc: 83–98, Sen: 58–100, Spe: 55–100
		Microscopy	GLEM features [91]	C	Acc: 61–68, Sen: 53–74, Spe: 63–68
Vascular system	Atherosclerosis	Microscopy	First-order statistics and GLCM features [332]	C	Acc: 90, Sen: 91, Spe: 92
		OCT	First-order statistics features [333]	C	Sen: 53–100, Spe: 93–97
	Carotid atherosclerosis	Ultrasound	Discrete and stationary wavelet and Gabor features [334]	C	Acc: 35–90, Sen: 27–90, Spe: 33–88
		Ultrasound	First-order statistics features [335]	C	*n/a*
		Ultrasound	GLCM, Laws, and fractal features [166]	C	*n/a*
		Ultrasound	LBP, GLCM, GLRLM, and Fourier features [152]	C	Acc: 74–90, Sen: 59–83, Spe: 76–95

† Performance rounded to zero decimal places. For consistency, only common metrics are shown and, the most common names used. Acc: accuracy; AUC: area under the receiver operating characteristics (ROC) curve; Pre: precision; Sen: sensitivity; Spe: specificity. n/a: not applicable.

with neoadjuvant chemotherapy and radiation therapy were evaluated before resection. Survival models that included CT texture features, besides identified changes in oesophageal wall thickness, performed better than those that included morphologic assessment alone. Texture analysis has also been applied to PET images for radiotherapy planning [338] and response assessment in renal cell cancer metastases treated with tyrosine kinase inhibitors [217].

Multiple studies have evaluated the response of different tumours and cancers to therapy using texture feature, for instance,

in lung cancer (first-order statistics and GLCM features [339]), in liver metastasis (GLCM features [340]), and colorectal cancer (first-order statistics features [341]). In [342], treatment with antiangiogenic therapy and radiation therapy for soft-tissue sarcoma were evaluated with perfusion CT. In general, changes in tumour heterogeneity may be associated with treatment response. Quantitative image findings, texture features included, have been correlated to histopathological results at surgical resection by comparing pre- and post-treatment metrics.

The active research on oncological applications of texture analysis shows the potential of using multiple texture features as a prognostic biomarker in the diagnosis, characterisation, and response assessment of different types of cancer.

B. Neuroimaging

Brain tumours' characterisation is one of the earliest texture analysis applications in neurology [220], [297]. In addition to its neuro-oncological applications, texture analysis is a promising quantitative biomarker in general neurology. When it comes to neuroimaging, MRI is the leading imaging modality. Texture analysis of MRI images is widely used to find biomarkers for different disorders such as epilepsy, multiple sclerosis, and Alzheimer's disease.

Epilepsy is a neurological disorder characterised by seizures. Texture analysis has been used in epilepsy to detect the lesions responsible for seizures, such as cortical dysplasia and hippocampal sclerosis. Statistical-based methods (GLCM features [80], [85]) and the wavelet transform [192] have been used in this field.

Multiple sclerosis is an inflammatory disease of the central nervous system that damages the insulating myelin sheath around the brain's axons and spinal cord. In the early stages of multiple sclerosis, the inflammation can be identified using T1-weighted MRI. However, in the advanced stages, the conventional MRI markers are not particularly helpful for disease monitoring [343]. Texture analysis can help in this regard, having been used in several studies for identifying active multiple sclerosis lesions and monitoring disease progression [64], [143]. In the early stage, multiple sclerosis lesions are classified by GLCM features [300]. In a subsequent work [64], additional texture features were extracted from the GLCM, GLRLM, the gradient matrix, the auto-regressive model, and the wavelet transform. This work suggested that a combination of features is more effective than a single-feature assessment for multiple sclerosis classification. Some works demonstrate the correlation of texture features to the changes associated with multiple sclerosis patient's disability [344].

Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the most common cause of dementia. The definitive diagnosis of AD is obtained only from an autopsy or brain biopsy. Even though no tests are available for a definite AD diagnosis *in vivo*, texture analysis can play a role in AD diagnosis and monitoring. In a pioneering work in 1998 [345], GLCM features were computed from MRI to study AD. Since then, MRI texture features have been widely applied to study this disorder [65], [74], [164], [290], [291]. In [346], the GLCM and the GLRLM were used to differentiate between Alzheimer's disease and Lewy-body dementia, the second most common cause of dementia after AD. In addition to 2D texture methods, some research groups have used 3D GLCM and GLRLM features from MRI images [347] and local 3D filter responses [290] as texture features to study AD. Notably, texture analysis studies on this disorder are not restricted to MRI imaging applications. Research has been extended to texture analysis of other imaging modalities such as PET [293], single-photon emission computer tomography (SPECT) [294], and optical coherence tomography (OCT) [348].

Texture analysis in neurology is not restricted to the disorders mentioned above but also applied to Parkinson's disease [301], ischemic stroke [289], amyotrophic lateral sclerosis [78], and Machado-Joseph disease [76].

C. Texture Features in 3D Biomedical Imaging

Volumetric texture is defined in the 3D spatial domain. Examples include medical images acquired by volumetric data acquisition devices, such as tomographic imaging techniques (CT, PET, and OCT), confocal imaging, and MRI.

Texture analysis of 3D data has been introduced as one of the emerging needs within the medical imaging and diagnostic radiology field [287]. Despite this demand, only a few methods have been developed to analyse 3D data, mainly due to 3D image analysis's computational cost. The developed 3D methods are usually the extensions of existent 2D popular methods, even though the extension of 2D methods to 3D, in general, is not straightforward and raises several challenges related to translation, scaling, and rotation invariances.

The GLCM method can be simply extended to 3D by considering three-dimensional vectors [349]. In [291], GLCM texture features were extended to define texture features on a voxel-by-voxel basis for 3D brain MRI acquisitions and provided a useful 3D statistical map to study cerebral pathology in neurology. Other texture analysis methods such as those based on the wavelet transform [350], Markov random fields [351], the GLRLM method [352], Gabor filters [353], the Wold decomposition method [202], and the LBP method [354], have been extended to 3D as well. Three-dimensional filtering [355] and 3D model-based methods [356] have also been proposed to extract 3D texture features.

3D texture analysis methods encompass rich information on the internal structures of objects by using all data dimensions. Two-dimensional texture analysis methods are usually less discriminative than 3D ones because one of the data space dimensions is ignored, therefore hampering the full exploitation of the information available. In [357], the performance of 3D texture analysis methods in biomedical image analysis has been analysed and reviewed.

Based on the success and attention that 2D texture analysis methods have obtained in biomedical imaging and the improved performance of 3D methods over 2D approaches, 3D texture analysis is expected to receive further research attention in the biomedical field.

D. Remarks

A wealth of imaging modalities are used in biomedical imaging depending on disease type and the biological tissues and organs involved. The limitations of the different image acquisition processes imply some constraints that need to be considered while choosing an adequate texture analysis approach.

MRI can be highlighted as one imaging modality where texture analysis methods have been most widely applied in recent years. The main issues affecting texture that must be considered when dealing with MRI data are noise, partial volume averaging, intensity non-uniformity, inter-slice intensity variation, and lack of intensity standardisation [358].

These issues can be mitigated by the proper choice of the texture analysis method to apply. Texture methods that are robust to noise can overcome the noise-related challenges in MRI data, for example. Illumination-invariant texture features can address the problems arising from intensity non-uniformity, inter-slice variability, and intensity non-standardisation. In [66], the sensitivity of different texture features (such as the GLCM, the GLRLM, the absolute gradient matrix, the auto-regressive model, and wavelet features) to variations in the MRI equipment and imaging protocols used, have been studied. The authors demonstrated that these texture features are relatively robust to several imaging variations and that a proper choice of robust texture features can address the issues mentioned earlier.

Some acquisition parameters in the CT imaging modality affect attenuation or pixel relationships, reflecting in texture-based metrics. It has been suggested that first-order statistical texture features may be less affected by these CT acquisition's changes [359].

In PET, the spatial resolution is low, which yields less robust texture information in small regions. Similarly, in ultrasound and OCT, noise-robust texture analysis approaches are the most appropriate due to speckle noise.

Biomedical image analysis relies on an immense range of texture analysis methods. The general trend is to use statistical-based methods such as the GLCM [64], [65], [72]–[82], [84]–[88] and the LBP methods [92], [99]–[104]. The next most popular approaches are spectral methods such as the wavelet transform [64], [82], [134], [192] and Gabor filters [159]–[162]. Nevertheless, for medical imaging classification systems (for instance, in [134], [164], [214], [334]), several different texture analysis features are combined since each conveys complementary information from the same image.

Besides handcrafted features, learned features also show a particular potential in medical image analysis. Some examples include brain structure segmentation [360], mitotic event detection and cancerous tissue evaluation [361], and polyp detection [362]. The lack of comprehensive datasets in the medical imaging domain is the main challenge when using deep-learning-based texture features. Two approaches have been suggested to address this issue: transfer learning and fine-tuning [363].

In transfer learning, CNN models, pre-trained from datasets of natural images or a different medical domain, are used for new medical tasks. For instance, in [364], pre-trained CNNs on a non-medical dataset (ImageNet) were used as feature generators for different types of pathologies in chest X-rays. In [314] and [315], transfer learning techniques were used to diagnose COVID-19. In [315], three deep CNN models were tested to classify subjects into COVID-19 positive and negative groups. The models were established using 100 X-ray images from COVID-19 positive patients and healthy subjects. Due to the small size of the dataset, transfer learning techniques were applied from the ImageNet database.

For medium-sized datasets, fine-tuning schemes that use a pre-trained CNN as initialisation of the network can be applied. In [362], the potential of fine-tuned CNNs in the context of medical image analysis was investigated. The preference of fine-tuned CNNs, regardless of the size of the available training sets, is well-demonstrated by its use for the most common medical imaging tasks (lesion detection, image segmentation, and image classification) from three different imaging modalities: CT, ultrasonography, and optical endoscopy.

Like the handcrafted features, features from deep-learning techniques can also be used alone or combined with other feature sets, both handcrafted and learned. An example along this line can be found in [168], where handcrafted features were combined with a pre-trained CNN model for bio-image classification. Further examples can be found in [295], [306], [318], and in Table X.

IV. Summary

Numerous approaches for the quantification and characterisation of texture have been proposed over the years. The focus of this paper, in the first part, was to provide an updated survey of texture analysis methods. As a comprehensive survey, the reader was introduced to an extended and granular categorisation of the texture analysis methods covering different aspects and trends in the field.

A thorough review of the handcrafted texture analysis methods was provided, covering both classical approaches and emerging categories. The learning-based approaches in texture analysis were addressed, covering the deep-learning processes and pointing out the use of high-performance CNNs in texture analysis. A list of integrative approaches, which present a well-balanced trade-off between different methods, was also compiled.

The importance of texture analysis techniques is supported by their application to many different problems and application fields, of which one of the leading applications fields is biomedical imaging. Quantitative measures of biomedical textures are expected to provide powerful diagnosis tools for several diseases. A list of the major disorders in which texture analysis was used on their assessment, detection, and progression analysis, was presented. Texture analysis maximises the information obtained from biomedical images and has shown the potential for further development as a valuable clinical tool. Such potential in oncology and neurology imaging was discussed throughout the second part of this paper.

Different texture analysis approaches have been applied, to a large extent, in 2D medical image analysis. Methods concerning 3D texture and deep-learning approaches were also addressed as these are two promising directions in the field.

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